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Article

Spatio-temporal analysis of wildfires occurrence in the Mexican State of *Oaxaca*

Análisis espacio temporal de la ocurrencia de incendios forestales en el estado mexicano de Oaxaca

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Abstract

In this study, we modelled and analyzed hotspot events recorded by MODIS satellite during the last nineteen years in the Mexican state of *Oaxaca* using a hierarchical Poisson Bayesian model. Our approach models the number of forest fires in space, time and the interaction of both and considers environmental variables. According to our results, some environmental variables can explain some of the observed Spatio-temporal variations, such as the temperature of the driest quarter, average wind speed, enhanced vegetation index values, and the occurrence of *El Niño*-Southern Oscillation. The analysis identified two spatial cluster regions: the first covers the *Sierra Juárez* up to the Isthmus of *Tehuantepec*, and the second covers the *Sierra del Sur*. Additionally, the temporal term in our model suggests that the number of events has increased by approximately 42.2 % in the last two decades. In conclusion, our results prompt that forest fires increased not only spatially but also in temporarily. These findings are alarm signals because if the trend continues, hundreds of new hectares of forest and its biodiversity will be threatened in the following decades, affecting too economic activities and people's health living in rural and urban areas of *Oaxaca*. This study can be a primary analysis in designing more efficient fire management programs to mitigate the impacts of altered fire regimes in *Oaxaca*.

Keywords: Biodiversity loss, carbon emissions, hotspots, satellite observation, spatial clustering, wildfires.

Resumen

En este estudio, se modelan y analizan los eventos de incendios forestales registrados en los últimos 19 años por el satélite de observación *MODIS* en el estado de Oaxaca; para ello, se utilizó un modelo *Poisson* jerárquico bayesiano, el cual modela el número de incendios forestales espacial y temporalmente, así como la interacción de ambos. De acuerdo con los resultados, algunas variables ambientales como la temperatura del trimestre más seco, la velocidad media del viento, el índice de vegetación mejorado y la ocurrencia del fenómeno El Niño-Oscilación del Sur, explican parte de la variabilidad espacio-temporal observada. Derivado del análisis, se identificaron dos grupos espaciales: el primero cubre desde la Sierra Juárez hasta el Istmo de Tehuantepec, y el segundo abarca la Sierra Sur. Adicionalmente, el término temporal sugiere que el número de eventos se ha incrementado en aproximadamente 42.2 % en las últimas dos décadas. Los resultados indican que los incendios forestales se han incrementado tanto espacial como temporalmente. Estos hallazgos son señales de alarma, dado que si la tendencia continua, en las siguientes décadas cientos de nuevas hectáreas de bosque y su biodiversidad serán amenazadas a causa de los regímenes de fuego alterados, que también afectará las actividades económicas y la salud de los habitantes de las áreas rurales y urbanas del estado. La información generada puede ser un punto de partida en el diseño de programas más eficientes para mitigar el impacto de los incendios forestales en Oaxaca.

Palabras clave: Pérdida de biodiversidad, emisión de carbono, focos de calor, observación satelital, agrupamiento espacial, incendios forestales.

Introduction

Wildfires are one of the most critical factors that have shaped and changed our planet's ecosystem and biodiversity, starting millions of years ago. In many regions of the world, those events are caused by a combination of natural sources such as lightning and the availability of forest fire fuel caused by marked dry seasons in certain months of the year. For example, 40 % of the vegetation types in Mexico are fire-maintained (Rodríguez, 2014). In some tropical forests, fires occur every dry season and make tree species exhibit adaptive traits to fires, playing an ecological role (Nasi *et al*., 2002). Even more, humans are responsible for between 75 % to 96 % of them, directly or indirectly, deliberately or through carelessness (Hirschberger, 2016).

The expression of fire as an ecological factor in forest ecosystems is through fire regimes (the pattern of repeated fires expressed as frequency, season, type, severity, and areal extent in a landscape) (Scott *et al*., 2014). It is estimated that 61 % of the ecoregions of the planet have degraded or very degraded fire regimes, so although fire plays a crucial role in maintaining many ecosystems, because of human actions, fire is behaving differently today than at any other time in human history (Shlisky *et al*., 2007). On a global scale, the alteration of fire regimes is a significant source of greenhouse gas emissions. At a regional level, fires impact biomass stocks, the hydrological cycle, and people's health and may significantly affect the biodiversity in forests. According to Nasi *et al*. (2002), in the latter part of the twentieth century, changes in the human-fire dynamic and an increase in *El*

Niño-Southern Oscillation frequency have led to a situation where fires are now a significant threat to many forests and the biodiversity therein. *El Niño* anomaly particularly leads to hot and dry conditions over many fire-prone regions globally, which can increase burned area (Burton *et al.*, 2020). From people's health point of view, bushfire smoke can affect millions of people, constituting a major public health problem during bushfire smoke episodes (Chen *et al.*, 2006; Dennekamp and Abramson, 2011).

Technological advancements make it possible to monitor huge areas through extensive satellite data. One application is the detection of active fires (hotspots), which is commonly based on the middle infrared (MIR) spectral region (3-5 μm) that implies a spectral radiance at the temperature of burning vegetation (500 to 1 000 K), which is higher than average Earth temperatures (300 K), efficiently discriminating the active fires (Chuvieco, 2008). The most important sensor is the Moderate-Resolution Imaging Spectroradiometer (MODIS) aboard the Aqua and Terra satellites, which identifies "fire pixels" of 1 km^2 in size (on average). According to Müller *et al.* (2013), the size of detectable fires depends on fire temperature, area, vegetation cover and sensor viewing angle.

Observation and record of hotspots also allow researchers to study, analyze and answer scientific questions using Spatio-temporal data. The available data does not support a general increase in the burned area or global fire severity. Still, there is evidence, based on some regional scales, that there has been an increase in the number of events and the total area burned (Doerr and Santín, 2016). Therefore, it is plausible to analyze and model wildfire events regionally instead of globally. In Mexico, some research efforts have focused on understanding different aspects of wildfires from a causation (Avila-Flores *et al*., 2010; Antonio and Ellis, 2015; Pompa-García *et al*., 2018; Zúñiga-Vásquez and Pompa-García, 2019) and prediction point of view (Perez-Verdin *et al.*, 2014; Ibarra-Montoya and Huerta-Martínez, 2016; Galván and Magaña, 2020; Monjarás-Vega *et al*., 2020; Ruíz-García *et al*., 2022).

Oaxaca is the most biodiverse state in Mexico. It harbors almost half the plant species and vegetation types in the country, as well as 40 % of mammal species, 63 % of birds, 26 % of reptiles and 23 % of river fish reported for Mexico (Oviedo, 2002). *Oaxaca* is located in southwestern Mexico, bordered by the states of *Puebla*, *Veracruz*, *Chiapas* and *Guerrero,* with the Pacific Ocean to the south (Figure 1). The state is crossed by tropical dry forests harboring up to 70 % of plant species living there as endemic. According to the results obtained based on data from 2000 to 2012, *Oaxaca* is in the top five states with higher emissions of black carbon (4 557-6 309 $t \cdot year^{-1}$) and organic carbon (48 441-70 663 $t \cdot year^{-1}$) from wildfires in Mexico (Cruz *et al.*, 2014). In the last technical report from Conafor, in 2019, *Oaxaca* figured in the top ten states with higher wildfire events and was in the top five with the greatest damaged surface (Conafor, 2020).

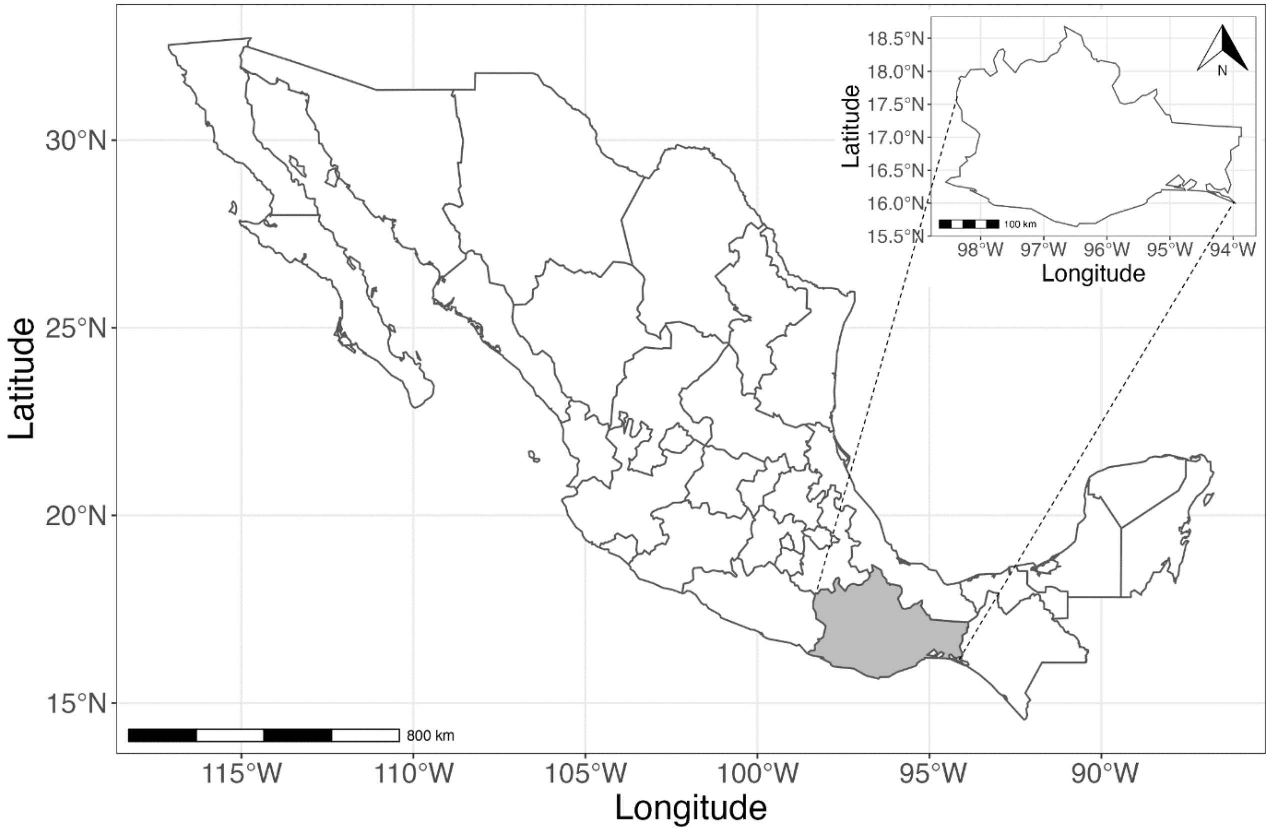


Figure 1. Geographical location of *Oaxaca* state in Mexico.

In this study, following the recommendation of Doerr and Santín (2016) about the need to conduct studies on local and regional scales and given the high biodiversity of *Oaxaca*, we analyzed the hotspot events retrospectively in the last 19 years (2001-2019) across the state of *Oaxaca*, Mexico. Our main goal was to explore and characterize the Spatio-temporal pattern of hotspot occurrence to investigate if hotspot patterns vary spatially and temporally across the state or whether the events are randomly dispersed in space and time. We think that hotspots are not spatially randomly distributed in our study zone. Instead, clusters are formed and can be partly explained as a function of some environmental variables such as temperature, precipitation, the slope of the terrain, wind speed and the type of vegetation. We also hypothesized a significant trend in the hotspots occurrence in space and time. Many studies have been carried out on forest fires in Mexico. Still, there has not been a unified approach that models spatially and temporarily and integrates and quantifies some environmental variables' effects on forest fire risk. Our approach can be extended in the future to include variables related to human activities that influence the hotspots distribution. As far as we know, this project is also the first to analyze hotspot data from two decades of satellite records in *Oaxaca*.

Material and Methods

Data and its general description

The hotspots database used in this analysis was obtained from the "Fire Information for Resource Management System-FIRMS" (NASA, 2020c). The records represent the center of a 1 km^2 pixel containing one or more daily fires recorded from January 2001 to December 2019 over the state of *Oaxaca*, Mexico. We discarded records with a low confidence level (lower than 30 %), and all events falling into the area that comprises the Pacific Refinery (located in *Tehuantepec*, *Oaxaca*, Mexico) were considered false alarms. The polygon shapefile delimiting the state of *Oaxaca* was downloaded from the Conabio geo-intelligence portal (Conabio, 2020). Each cell divided the state into a regular lattice of 10 km^2. The total number of hotspots' new records (not repeated) were registered in each cell for each year. This data for all the State and the nineteenth years constitute the Spatio-temporal data that were modelled through an appropriate statistical model that we discuss later.

Additionally, a database of standardised environmental (raw values minus the average and divided by its corresponding standard deviation) variables was generated at 1 km^2 spatial resolution. This database contains values of the Mean Temperature of the Driest Quarter (*TempDQ*, °C), Mean Precipitation of the Driest Quarter (*PpDQ*, mm), Mean Wind Speed (*WindSpeed*, m·s^{-1}), *Slope* (decimal degrees), Mean values of Enhanced Vegetation Index (*EVI*, dimensionless), and two indicator variables representing the occurrence of *El Niño*-Southern Oscillation and its counterpart *La Niña* in the previous year. Climatic variables were downloaded from the WorldClim-2 website (Fick and Hijmans, 2017) and correspond to mean values from historical data, while *Slope* was obtained from the Conabio geo-intelligence portal (Conabio, 2020). Average values of *NDVI* were calculated from raw data downloaded from the EarthData website (NASA, 2020b) through the AppEEARS application (NASA, 2020a).

Statistical model

We use a Poisson hierarchical model used for spatial lattice data, which has been used in similar applications (Boadi *et al*., 2015; Costafreda, 2017), where the response variable $y(s)$ is a random aggregate value (count) over areal unit s in time t. In our case, the study region was partitioned into $i = 1, 2, \ldots, 1\,124$ cells, and data are available for $t = 1, 2, \ldots, 19$

years. Let Y_{it} be the random variable denoting the number of hotspot/fire occurrences in area i at time t. Given that realization of Y_{it} can take values $y_{it} = 0, 1, 2, \ldots$ (count random variable), the first level of a hierarchy is:

$$Y_{it}|\lambda_{it} \sim Po(\lambda_{it}), i = 1, 2, \ldots, 1124, \ t = 1, 2, \ldots, 19 \qquad (1)$$

Where:

Po = Stands for a Poisson distribution wit λ_{it} as the rate parameter, which denotes the expected number of events in cell i at time t

The second level of hierarchy links predictors (that account for fixed effects, spatial components, time trend and time-space interaction) to λ_{it} corresponds to the function:

$$ln(\lambda_{it}) = \alpha + \boldsymbol{x}'_{it}\boldsymbol{\beta} + u_i + v_i + \gamma_t + \phi_t + \delta_{it} \qquad (2)$$

Where:

α = Represent the overall log-scale mean hotspot occurrences

$\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_7)'$ = Vector of fixed effects associated with environmental-variates $\boldsymbol{x}'_{it} = (x_{it1}, x_{it2}, \ldots, x_{it7})$

x_{itj} = Values of *TempDQ*, *PpDQ*, *WindSpeed*, *Slope*, *EVI*, and the two dummy variables denoting the occurrence of *El Niño* and *La Niña*

The purely spatial random effects are given by u_i and v_i, a structured spatial and an unstructured spatial effect, respectively. The exponential sum, $\zeta_i = exp(u_i + v_i)$, denotes the expected number of events per year for each cell explained only by spatial effects. γ_t and ϕ_t, represent a structured spatial trend and an unstructured spatial residual, respectively. Finally, δ_{it} accounts for space-time interaction.

For practical purposes, we fit the model (Equations 1 and 2) with the Bayesian statistical approach using the Integrated Nested Laplace Approximation (*INLA*) (Rue *et al*., 2009) in the R programming language (R Core Team, 2019). Therefore, prior (third level of the hierarchy) distributions are needed for all model parameters to complete the specification of the above models. For the overall log-scale mean, we assumed a non-informative uniform prior, i.e. $\alpha \sim Uniform$, and for each element of β, a diffuse Gaussian distribution with zero mean and arbitrary significant variance σ_β^2, i.e. $\beta_j \sim N(0{,}1000)$, $j = 1, 2, \ldots, 7$, to assign to α and β non-informative diffuse priors. The other parameters assumed to have normal distributions are the temporal effect $\phi_t | \sigma_\phi^2 \sim N(0, \sigma_\phi^2)$, the unstructured spatial heterogeneity effect: $v_i | \sigma_v^2 \sim N(0, \sigma_v^2)$, and the space-time interaction effect: $\delta_{it} | \sigma_\delta^2 \sim N(0, \sigma_\delta^2)$. For the u_i the effect, we used the intrinsic conditional autoregressive model (iCAR) (Besag, 1974), which represents the spatial dependence between nearby areas. iCAR is expressed as:

$$u_i|u_{-i},\sigma_u^2 \sim N\left(\frac{1}{N_i}\sum_{i=1}^{n} a_{ij}u_j,\frac{\sigma_u^2}{N_i}\right) \quad (3)$$

Where:

$u = \{u_1, \ldots, u_n\}$ and $u_{-i} = \{u_1, \ldots, u_{i-1}, u_{i+1}, u_n\}$. $N_i = N(i)$ is the number of cells that are first-order neighbors of area i (cells i and j are first orders neighbors if they share a common boundary; see Banerjee *et al*., 2015), and the a_i weights are constants and specified as $a_i = 1$ if cell i and cell j are neighbors, and $a_i = 0$ otherwise. The variance parameter σ_u^2 controls the amount of variability of the random effects and is estimated from the data.

The structured temporal effect is dynamically modelled using a 2nd order random walk (RW-2): $\gamma_t|\gamma_{t-1},\gamma_{t-2} \sim N(2\gamma_{t-1} + \gamma_{t-2},\sigma_\gamma^2)$. RW-2 is the easiest way to model non-linearities in the temporal trend. For the variance hyper-parameters $(\sigma_\phi^2,\sigma_v^2,\sigma_\delta^2,\sigma_u^2,\sigma_\gamma^2)$, we assigned independent Inverse-gamma distributions, $IG(a = 1, b = 0.00005)$. Values of a and b have been suggested as a sensible choice by Blangiardo and Cameletti (2015).

Results and Discussion

Table 1 presents the posterior mean, the posterior standard deviation and the posterior 95 % credible interval of each element of ($\boldsymbol{\beta}$) and α. Only four of seven environmental variates had associated parameters considered statistically significant (those whose intervals do not contain zero) for explaining the log rate of hotspot events. These were parameters associated with *TempDQ* and *EVI* variables, with positive effects and negative signs with *WindSpeed* and *El Niño*. Parameters are easily interpreted on the natural scale, i.e., $\exp(\hat{\beta})$. For example, an increase of one standardized unit of *TempDQ* or one unit of *EVI* implies an increase of 78.1 % ((1.781-1)×100)) and 34.9 % in the risk of having hotspot events, respectively. Other studies in Mexico also documented that temperature increases the risk of forest fires (Perez-Verdin *et al.*, 2014; Antonio and Ellis, 2015). On the other hand, average *EVI* values give us information about biomass stock potentially available as forest fuel in dry seasons; therefore, as *EVI* values increase, the danger effect of forest fires increases.

Table 1. Summary statistics for fixed effects.

Environmental variable	Parameter	Mean	Standard deviation	95 % credible interval	*Exp (mean)*
Intercept	α	0.153	0.149	[-0.192, 0.41]	1.165
*TempDQ**	β_1	0.577	0.122	[0.337, 0.817]	1.781
PpDQ	β_2	-0.008	0.126	[-0.255, 0.238]	0.992
Slope	β_3	0.013	0.061	[-0.106, 0.132]	1.013
*WindSped**	β_4	-0.348	0.122	[-0.588,-0.108]	0.706
*EVI**	β_5	0.299	0.062	[0.178,0.419]	1.349
*Niño**	β_6	-0.523	0.186	[-0.836,-0.088]	0.593
Niña	β_7	-0.248	0.193	[-0.591,0.184]	0.78

*Statistically significant variables.

In contrast to what is expected, an increase of one standardized unit in *WindSpeed* gives 29.4 % ((1-0.706)×100)) less risk of experimenting with a wildfire event. A possible explanation could be that wind is a fire danger factor, i.e. as its speed increases, the fire propagation rate also increases. Still, wind only causes fire directly when strong winds generate secondary fires during wildfires. Also, wind speed may interact with other variables not accounted for in this analysis. The effect associated with *El Niño* requires special attention. When the *El Niño* phenomenon is observed in the previous year, the risk of hotspot occurrence is reduced by about 40.7 %. This may be explained by the fact that *El Niño* causes more precipitation in Mexico in the winter (Bravo-Cabrera *et al*., 2017). Therefore in the dry season (spring of the following year), there is less dry vegetable fuel.

Figure 2 depicts the posterior mode of the main spatial effect $\zeta_i = exp(u_i + \nu_i)$. Two clusters can be formed with the highest values of the main spatial effect. The first one is caused by a band from the northwest to the southeast in *Oaxaca* State, beginning in the *Sierra Mazateca*, going through the *Sierra Juárez* close to the center of the state, and extending up to the *Sierra Mixe* and the Isthmus of *Tehuantepec*. It is important to note that this area is the end of the *Sierra Madre Oriental* that crosses all of the Mexican Republic. At this latitude, it is conformed by tropical dry forest harboring up to 70 % of plant species living there as endemic. The highest values of the main spatial effect ($\zeta = \max\{\zeta_i\}$) is likely due to anthropogenic effects (slash-and-burn practices, cattle raising, illegal forest exploitation, and in general, land-use changes), as suggested by Galván and Magaña (2020), and not due to environmental variables. Some cells with high values of ζ close to *Veracruz* state (lower area of the *Papaloapan* river basin) are explained by extensive agriculture and cattle raising. In the neighboring state of *Chiapas*, the altered tree composition of many tropical deciduous forests results from centuries of forest fires and cattle and goat raising (Miranda, 2015).

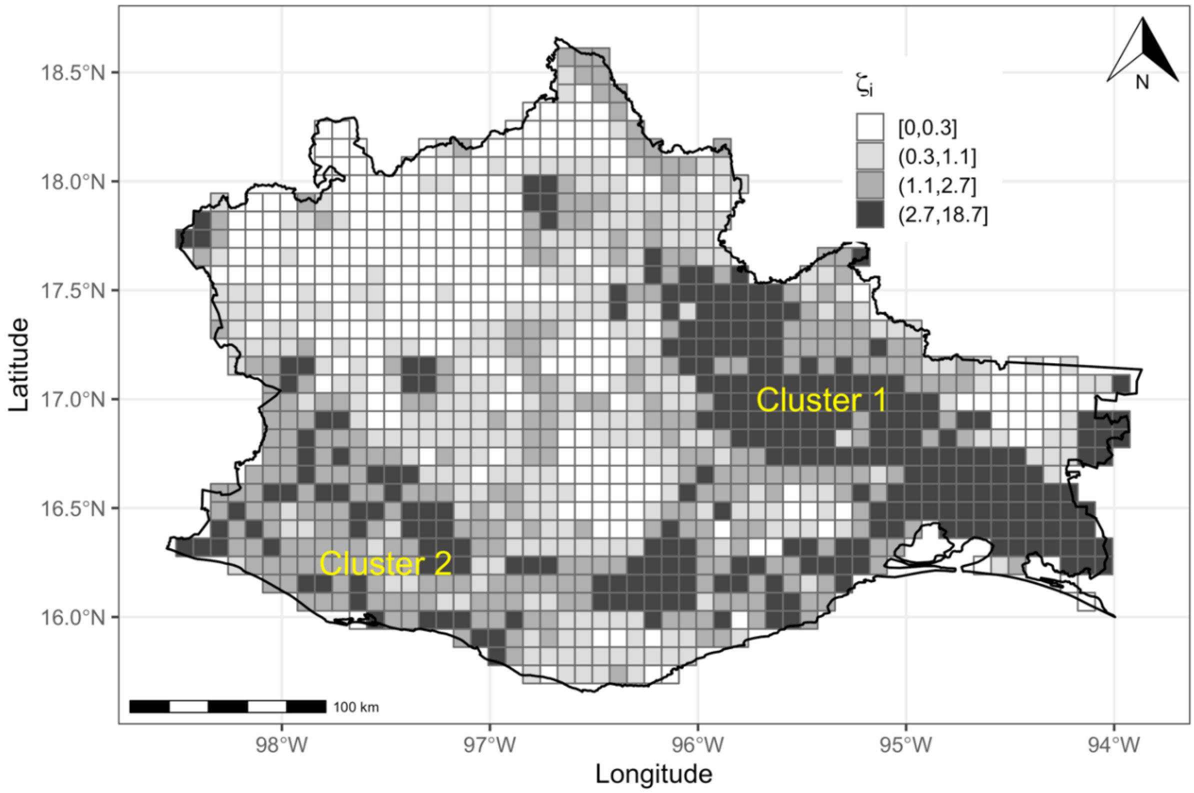


Figure 2. Posterior mode of the spatial main effect $\zeta_i = exp(u_i + v_i)$ of hotspot events in *Oaxaca*, Mexico.

Many original tropical deciduous forests in Mexico are a mix of fire-adapted and fire-sensitive tree species, and fire tends to select the former and eliminate the latter (Rodríguez *et al*., 2019). It is important to note that the *Chimalapas* jungle, a rainforest region with high biodiversity, has low spatial effect values, although the neighboring areas exhibit high values. The low values can probably be explained by the conservation efforts of the native indigenous population in that region (in 1998 -an extreme fire season in Mexico- this region was severely affected by extensive wildfires).

The second cluster goes from the southwest (adjoining the state of *Guerrero*) to the southeast of the state, an area that comprises the *Sierra Madre del Sur*. This region is made up of dry, warm forests and temperate mountain ranges, and probably high values of the main spatial effect are also due to the anthropogenic impacts. Both clusters identified in this study were also identified by Zúñiga-Vásquez *et al*. (2017), integrating data for the whole Mexican territory.

Table 2 presents summary statistics such as the mean, standard deviation, and 95 % credible interval for hyper-parameters. Computing $f_{spatial} = \sigma_u^2/\sigma_v^2 = 0.9998$, tells us that 99.98 % of the observed variation can be explained by the structural, spatial term u.

Table 2. Summary statistics for hyper-parameters.

Hyper-parameter	Mean	Standard deviation	95 % credible interval
σ_u	2.161	0.078	[2.039,2.339]
σ_v	0.03	0.017	[0.012,0.075]
σ_γ	0.114	0.067	[0.025,0.277]
σ_ϕ	0.216	0.087	[0.108,0.443]
σ_δ	0.762	0.007	[0.748,0.776]

Figures 3a and 3b show the posterior mode of structured γ_t and unstructured ϕ_t time effects, respectively, reported on the natural scale, i.e. exponentiating. We also reported the 95 % highest posterior density interval (*HPDI*) for both quantities. Figure 3a shows that the structured effects from 2001 to 2005 increased. After that, the trend was stable for ten years, marginally declining, but from 2015 to 2019, a new incremental trend was visible. The increment from 2001 to 2019 of the structured effects was 42.2 %. It would be essential to confirm this alarm signal in the future; we know that climate change and global warming are affecting wildfire patterns in some regions, perhaps locally incrementing the occurrence throughout space and time. According to projections of Senande-Rivera *et al.* (2022), the global area with frequent fire-prone conditions will increase by 29 % (25 % in temperate zones) at the end of the 21st century. An effect of the increase in forest fires in the future may be to raise the loss of cover in forest areas altering the hydrological processes (Ruíz-García *et al.*, 2022), besides social and environmental impacts. On the other hand, the unstructured effect term (Figure 3b) displayed some fluctuation around one, as was expected because this term represents the temporal variation (residual) not explained by the model.

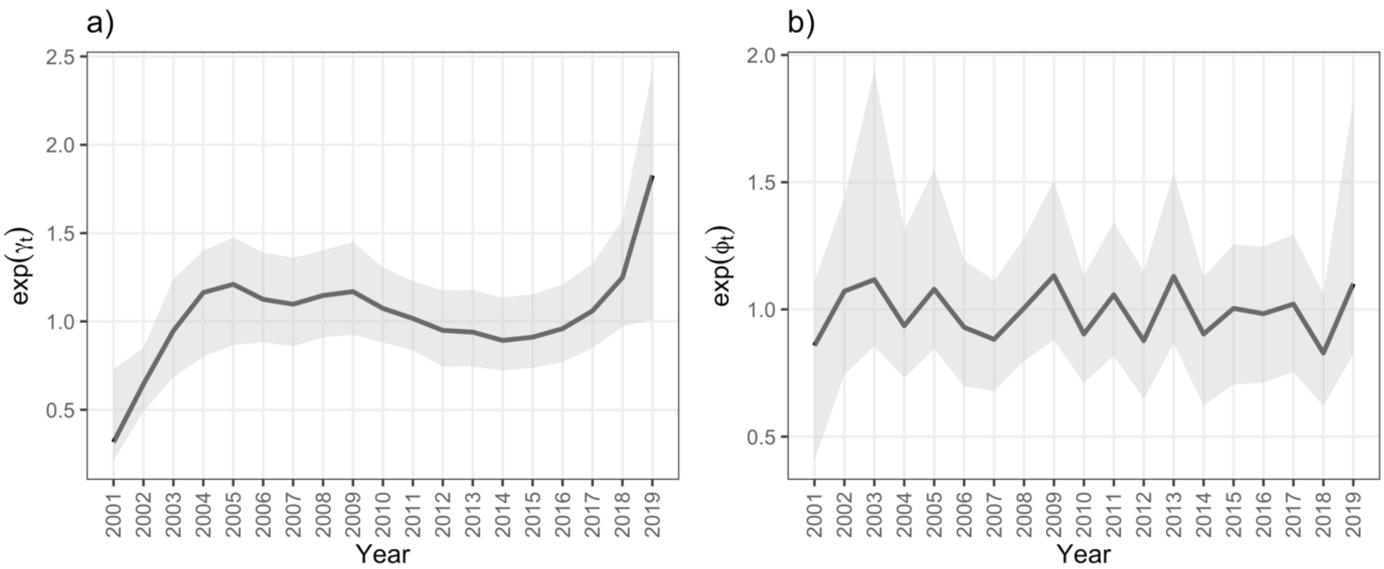
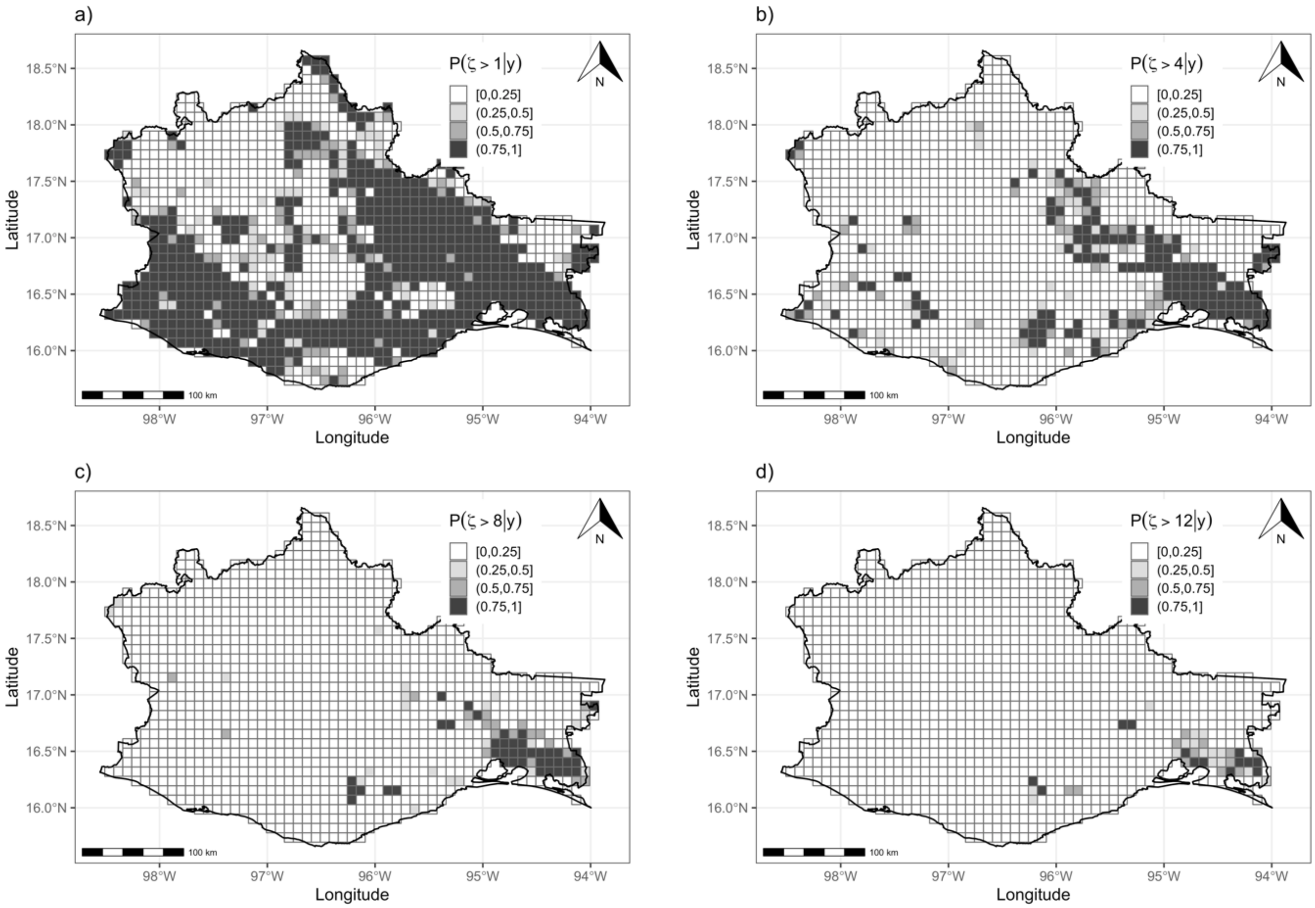


Figure 3. Posterior mode and credible temporal trend interval for hotspot events in *Oaxaca*, Mexico. In a) the temporally structured effect $exp(\gamma_t)$; b) the unstructured effect $exp(\phi_t)$.

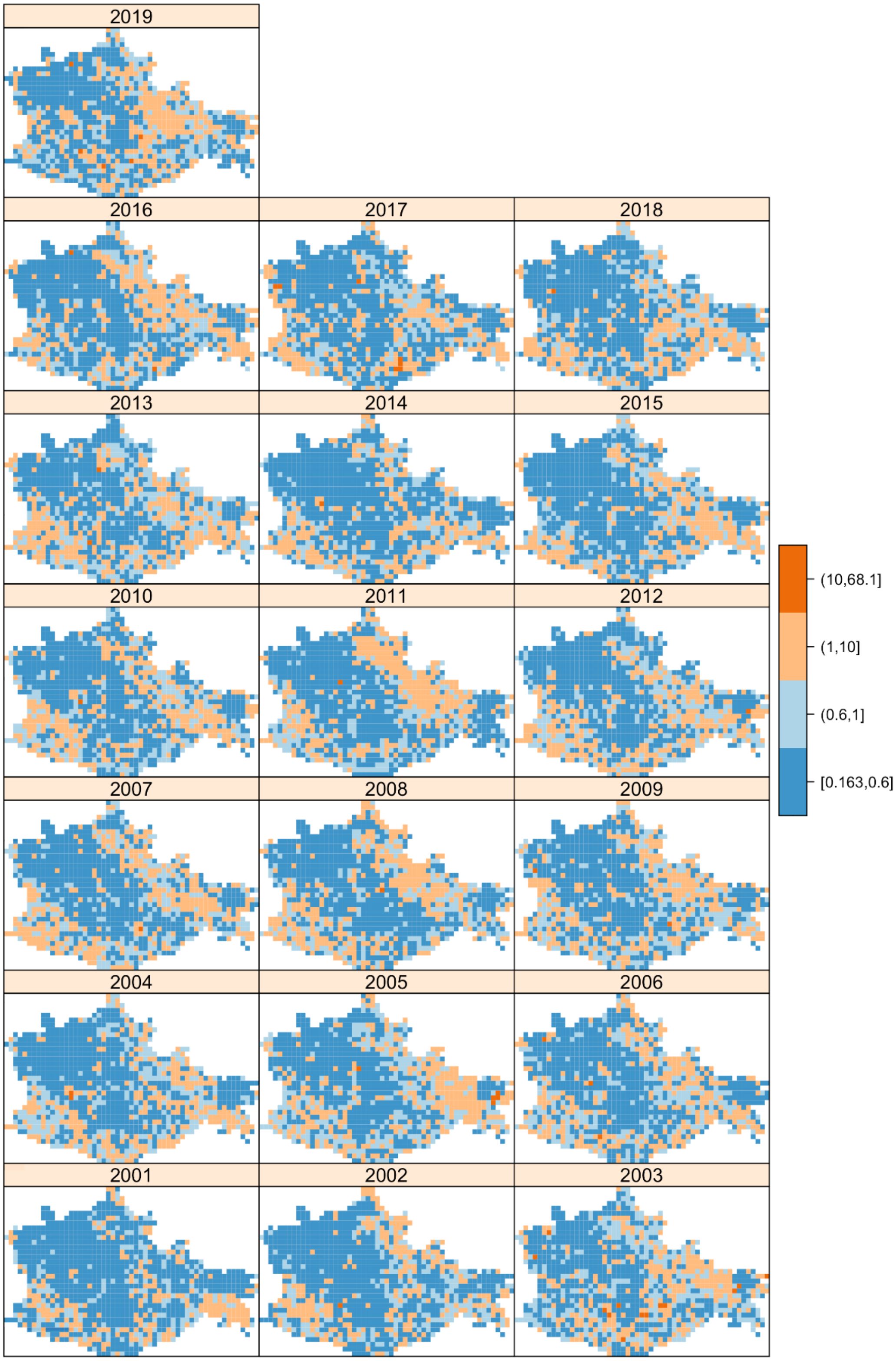
We depict the exceedance probabilities in figures 4a-4d. Exceedance probabilities are the probability that the relative rate of area i is higher than value c, mathematically $P(\zeta_i > c|\boldsymbol{y})$. Note that almost half of the state has a probability greater than 0.75 (75 % of chance) of having at least two hotspot events in a year (Figure 4a). In the most extreme cases, there are few cells located in the Isthmus of *Tehuantepec* that have at least a 0.75 probability of exceeding 12 events per year (Figure 4d).



In a) for $c = 1$; b) for $c = 4$; c) for $c = 8$; d) for $c = 12$.

Figure 4. Exceedance probability $P(\zeta_i > c|y)$, for a relative rate of hotspots events in *Oaxaca*, Mexico.

The posterior mode for the space-time interaction term on the natural scale, i.e. $exp(\delta_{it})$, is depicted in Figure 5 for all cells and all years included in the analysis. When $exp(\delta_{it}) > 1$, this implies that cell i in year t had hotspot records greater than average ($\hat{\alpha} = 1.165$). On the other hand, when $exp(\delta_{it}) < 1$, the hotspot records were less than average. Note that through the years, orange and red-colored cells (with high values of $exp(\delta_{it})$) cover most of the area of the state from year to year. The increment in the number of orange and red-colored cells is small but visible. It is in line with the main temporal trend observed in Figure 3a, i.e. the number of events is increasing in space and in time, which is an alarm signal that demands to adopt more efficient fires management policies by the local and federal governments to reduce and mitigate the impact of altered fire regimes in *Oaxaca*.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(10,68.1]
(1,10]
(0.6,1]
[0.163,0.6]

Figure 5. Posterior mode of the Spatio-temporal interaction $exp(\delta_{it})$.

Conclusion

We performed a Spatio-temporal analysis of hotspot events recorded in the Mexican state of *Oaxaca* in the last nineteen years using data from the MODIS sensor to investigate whether forest fires are randomly dispersed throughout the state or clusters are formed. We quantified the effect in hotspots number in areal units as a function of some environmental variables, the purely spatial effect and the temporal trend using a Bayesian hierarchical Poisson model.

According to our results, environmental variables such as the mean temperature of the driest quarter, mean values of the Enhanced Vegetation Index, mean wind speed, and *El Niño*-Southern Oscillation occurrence can explain some of the observed spatial variations in hotspot events. From the spatial component of the statistical model, hotspots are clustered mainly throughout the *Sierra Juárez* and going up to the Isthmus of *Tehuantepec*, but also all through the *Sierra del Sur* (towards the coast of the state). An alarm signal was revealed from our analysis: the structured temporal term shows an increasing non-linear trend of hots-pots number across the period analyzed of about 42.2 %, altering the fire regimes even more. The Spatio-temporal interactions parameter also confirms this tendency showing that the number of events is incrementing in space and time. Suppose the increment continues in the following decades. In that case, hundreds of new hectares of forest and the species living there will be threatened, including economic activities and people's health in rural and urban areas.

This work can be a starting point for further research to understand better the spatial and temporal distribution of forest fires and altered regimes in *Oaxaca*. By identifying the main clusters, the Conafor can design better logistics to act with opportunity reducing the environmental and socioeconomic impacts caused by wildfires. But also, with better logistics, the economic and technical resources needed to contest wildfires can be optimized.

Exceedance probability reveals some very local regions that expect a high number of events every year (>4 in a year), it would be interesting to answer from a causation point of view why this occurs and design practical mitigation actions. The incremental temporal trend discovered here can be reverted in many ways, such as the conscientization with complete and well-planned campaigns focused on rural populations that most interact with the forest. Technical training for farmers is also needed to make agricultural practices less risky in triggering forest fires. Illegal forest exploitation and land-use change can be effectively neutralized, generating profitable rural development activities such as ecotourism, agroforestry, and the incorporation of rural communities in the programs of payments for environmental services, among other things. A possible research project could point out how to generate perdurable rural development that inhibits those activities previously mentioned. From a statistical point of view, in the future, we could extend our analysis by including additional environmental and socio-economical variables to indirectly quantify the anthropogenic effects, poverty, and social inequality in the risk of forest fires and altered fire regimes.

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Conflict of interests

The authors declare that they have no conflict of interest.

Contribution by author

Bartolo de Jesús Villar-Hernández: original idea, accessing and cleaning datasets, coding and fitting the model and writing the manuscript; Sergio Pérez-Elizalde, Dante Arturo Rodríguez-Trejo, Paulino Pérez-Rodríguez: revision and discussion of the manuscript.

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