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Understanding wildfire occurrence and size in Jalisco, Mexico: A spatio-temporal analysis

Camila Toledo-Jaime [a], Carlos Díaz-Avalos [a,b,*], Somnath Chaudhuri [c,d,e], Laura Serra [d,e], Pablo Juan [d,f]

[a] Faculty of Sciences, National Autonomous University of Mexico, Mexico
[b] Research Institute in Applied Mathematics and Systems, National Autonomous University of Mexico, Mexico
[c] WorldPop Research Group, School of Geography and Environmental Science, University of Southampton, UK
[d] Research Group on Statistics, Econometrics and Health (GRECS), University of Girona, Spain
[e] CIBER of Epidemiology and Public Health (CIBERESP), Madrid, Spain
[f] Department of Mathematics, IMAC, University of Jaume I, Spain

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A B S T R A C T

In recent years, the growing frequency and severity of wildfires, influenced by both human activities and climate change, have posed significant challenges worldwide. Among the regions most affected by wildfires in Mexico is the state of Jalisco, which has the largest accumulated burned area in the last five decades. In this paper, we present an in-depth analysis of the spatio-temporal patterns of wildfire occurrence and size in the state of Jalisco, spanning the period from 2001 to 2020. Our approach included modeling the spatial distribution of the area burned by wildfires, employing Bayesian methodology with Integrated Nested Laplace Approximation (INLA) and Stochastic Partial Differential Equations (SPDE). Our findings highlight the critical roles of vegetation, temperature, and human activities in shaping wildfire behavior. Additionally, our model suggests four distinct wildfire-prone regions within the state. The insights gained from this study can serve as a foundation for future research and localized studies, aiding in the development of more targeted and effective wildfire management strategies in Jalisco.

1. Introduction

Fire is a natural phenomenon present on Earth for millions of years (Bowman et al., 2009); its occurrence has varied over time due to changes in climate, vegetation, geology, and more recently, anthropogenic influence. Fire has also played a crucial role in the functioning and dynamics of many terrestrial ecosystems, acting as one of the primary forces of natural selection, influencing the evolution of various species and promoting biological diversity (Pyne et al., 1996; Jardel-Peláez et al., 2014).

A wildfire may be defined as the uncontrolled and unrestricted spread of fire in forested or wildland areas, such as those covered by forests, shrubs, natural grasslands, and other combustible vegetation (Pyne et al., 1996). Although wildfires play a central role in the composition, structure, and functioning of diverse ecosystems, the alteration of fire regimes, which includes disrupted historical patterns in fire frequency, intensity, and spatial distribution, poses a significant threat to biodiversity and ecosystem health. Beyond their ecological impact, wildfires have gained recognition as a significant societal concern, representing a threat to human settlements and economic activities across the globe (Reid et al., 2016; Zhang and Biswas, 2017). Wildfires also contribute to environmental challenges by emitting greenhouse gasses, primarily carbon dioxide (CO2), and releasing harmful particulate matter into the atmosphere (Wiedinmyer and Neff, 2007; Corona-Núñez et al., 2020)

In recent years, there has been an increase in the frequency and severity of wildfires in many regions of the world, often influenced by human activities and climate change (Flannigan et al., 1998; Jolly et al., 2015; Balch et al., 2017; Abatzoglou et al., 2019). This is also true for Mexico, where the total burnt hectares between 2011 and 2021 represented an increase of 123.72 % compared to the previous decade (Nacional Forestry Commission (Conofar, 2022). One of the regions most affected by wildfires in Mexico is the state of Jalisco which, according to Conafor (2022), has the largest accumulated burned area in

* Corresponding author at: Faculty of Sciences, National Autonomous University of Mexico, Mexico
E-mail address: carlos@sigma.iimas.unam.mx (C. Díaz-Avalos).

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the last 50 years; the high forest coverage, particularly of pine and oak forests (both highly flammable), combined with the climatic and topographic conditions, increases the state's susceptibility to forest fires. Additionally, human factors such as large-scale agricultural production, urbanization, poor practices involving the use of fire, and the cultivation of illicit crops raise the risk of wildfire occurrence (Jardel et al., 2006; Semadat, 2021).

Fire is a spatio-temporal process driven by controls acting across a range of scales (Falk et al., 2011). At a local scale, fire behavior is the result of complex interactions between fuel conditions, weather, topography, and ignition sources (Heyerdahl et al., 2001; Falk et al., 2011). On the other hand, regional climate is the dominant factor affecting wildfires at broader scales (Yin et al., 2020; Zhao et al., 2021). Climate can directly influence wildfires by controlling the moisture content of fuel, and indirectly by influencing coarse-scale spatial variation in vegetation composition and structure, which in turn determines the size, quantity, and arrangement of fuel load (Heyerdahl and Alvarado, 2003). Moreover, recent research (Corona-Núñez and Campo, 2023) sheds light on the intricate interplay between climate, socioeconomic drivers, biomass burning, and carbon emissions, offering insights into global wildfire controls.

Understanding the drivers behind wildfire incidence is crucial for effective management and mitigation strategies, and even though there is extensive research on the relationship between wildfires and multiscale environmental factors (Heyerdahl et al., 2001; Gill and Taylor, 2009; Falk et al., 2011; Parks et al., 2012; Zhao et al., 2021) there is limited information about the effect of anthropogenic and biophysical controls on the burned area and number of wildfires in Jalisco.

Studying the spatial distribution of wildfire size and occurrence is also relevant as it provides insight into high-risk areas, which enables the prioritization of resources and the assessment of ecological impacts, including changes in vegetation composition, species diversity, and habitat structure. Modeling the spatial incidence of wildfires, along with their final size, is an efficient way to detect trends in their spatiotemporal patterns and to identify spatial clustering, which could indicate the presence of high-risk factors (Serra et al., 2014a). Spatial models also help to disentangle the relative roles of different controls on fire behavior and offer an understanding of wildfire predictability (Pimont et al., 2020; Castel-Clavera et al., 2022), which is of increasing importance, especially in the context of ongoing global warming and climate change (Zhao et al., 2021).

Previous studies have used statistical methods to model wildfire risk, considering risk as the probability that a wildfire ignites at some location inside the study area (e.g. Díaz-Avalos et al., 2001; Amatulli et al., 2007; Hering et al., 2009; Yang et al., 2012; Serra et al., 2014a, b); however, most of these studies have not examined the burned area caused by each wildfire (Díaz-Avalos et al., 2016). Additionally, little work has been done to investigate the spatio-temporal distribution of wildfires in Jalisco at a regional scale. Most research has focused either on analyzing wildfire patterns and drivers at a local extent, commonly inside natural reserves (Balcázar, 2011; Cerano-Paredes et al., 2015; Ibarra-Montoya and Huerta-Martínez, 2016; Jardel et al., 2006) or at the national scale (Rodríguez-Trejo, 2008; Jardel-Peláez et al., 2014; Corona-Núñez et al., 2020; Neger et al., 2022; Montoya et al., 2023). Our study addresses this critical research gap through the analysis of wildfire incidence at the state level, providing a comprehensive perspective that bridges the gap between local and national wildfire studies.

In this paper, we present an in-depth analysis of the spatio-temporal patterns of wildfire occurrence and size in the state of Jalisco, Mexico, spanning the period from 2001 to 2020. Our approach included modeling the spatial distribution of the area burned by wildfires, with the final size of each wildfire serving as the response variable (Aragó et al., 2016; Díaz-Avalos et al., 2016). Under this approach, observed patterns of fire ignition are viewed as realizations of a spatio-temporal point process, where points correspond to the starting locations and times of wildfires, and the total burnt surface is used as a mark for the points (Pimont et al., 2020). Our purpose was to find and fit statistical models, employing Bayesian methodology, that could provide a comprehensive analysis of wildfire size, spatial distribution, and insights into the principal drivers influencing fire dynamics.

Specifically, our study aimed to achieve the following objectives: 1) Describe the temporal and spatial patterns of wildfires in Jalisco, including their number, size, interannual variation, and impact on vegetation cover during the 2001–2020 period; 2) Analyze the influence of key factors, including climatic variables, topography, fuel characteristics, land cover, and human activities, on wildfire occurrence, size, and spatial distribution within the state; 3) Identify high-risk areas within the study site, to enhance our understanding of wildfire vulnerability.

To achieve our objectives, we utilized remote sensing and geospatial analysis techniques. Data analysis and point pattern modeling were performed using the R software (R Core Team, 2021). We employed the Integrated Nested Laplace Approximation (INLA) methodology in combination with the Stochastic Partial Differential Equation (SPDE) framework (Rue et al., 2009; Lindgren et al., 2011; Díaz-Avalos et al., 2016; R-INLA Project, 2020) to fit parametric models to observed wildfire patterns, incorporating relevant available covariate information.

2. Methods

2.1. Study area

The state of Jalisco, depicted in Figure S1 in the supplementary material, is located on the central western coast of Mexico (18°58' ~ 22°45'N, 101°28 ~ 105°43'W), and it extends approximately 78,596 km^2, which represents 4 % of the Mexican territory (National Institute of Statistic and Geography (Inegi, 2013). The state's topography varies significantly, with an elevation range from 0 to 4300 m above sea level (Cuevas-Arias et al., 2008). Most of the state has a temperate climate with tropical humid summers; rainfall is strongly seasonal from June to October, and there is a dry, hot period from March to May (Cuevas-Arias et al., 2008). The mean annual temperature is 20.5°C, with the lowest values occurring in January and the highest in May (INEGI, 2013). The mean annual precipitation is around 850 mm per year although, in coastal areas, it can exceed 1000 mm (INEGI, 2013). The geographical location, heterogeneous relief, and climatic gradient of Jalisco favor the establishment of diverse vegetation types. According to the National Forestry Commission (CONAFOR) the predominant vegetation covers in the region are agricultural land (30.3 %), tropical dry forest (19.2 %), oak forest (18.6 %), coniferous forest (11.6 %), induced vegetation (6.5 %) and natural grasslands (5.7 %). Notably, both oak and pine forests produce highly flammable litter, and wildfires are widespread in grasslands (Stavi, 2019). Furthermore, the role of fire in tropical dry forests stands out as a critical factor influencing biodiversity and carbon emissions (Corona-Núñez and Campo, 2023).

2.2. Wildfire burned area data

This study used satellite-based burned area observations derived from the product Fire-CCI v5.1, the latest burned area dataset of the European Space Agency's Climate Change Initiative (CCI) program. The pixel product comprises maps of global burned area at a 250 m resolution, generated from the MODIS red (R) and near-infrared (NIR) reflectances, together with thermal anomalies data (Chuvieco et al., 2018). The product is released monthly as a GeoTIFF file with three layers indicating the date of detection, the confidence level, and the land cover in the pixel detected as burned (Pettinari and Otón, 2020).

The database was accessed with a yearly resolution spanning from 2001 to 2020, utilizing the Google Earth Engine platform. Given that the Fire-CCI v5.1 product provides monthly burned area data, we integrated the maximum burned area within each 0.25-degree cell of the product grid; this approach allowed us to capture the largest wildfires that occurred within a year, considering that a single pixel might undergo multiple burn events throughout this period.

To enhance the analysis, we converted the GeoTIFF files to a vector format in a Geographic Information System (GIS), enabling us to represent individual fires as burned polygons instead of individual burned pixels. To consolidate multiple polygons into a single fire event, we employed two criteria: (a) if they shared borders and (b) if they occurred within a maximum of three days apart, considering the Julian day associated with each polygon from the original product. It is important to note that there is a margin of error associated with this procedure, as it is possible for the same wildfire to be dispersed across an area rather than occurring as a continuous event; furthermore, it is conceivable for a single fire to spread for longer than three days, especially if it is of significant magnitude. Nevertheless, it is unlikely for both scenarios to happen frequently (Hawbaker et al., 2008).

The final product consisted of vector files that included the largest fire episodes detected for each year of the study period (Fig. 1). Each vector file was accompanied by its attribute table, providing information regarding the day of fire detection, the centroid coordinates, and the corresponding burned area.

2.3. Environmental data

2.3.1. Land cover

Landcover plays a crucial role in wildfire occurrence, size, and distribution. The type, amount, and arrangement of vegetation not only impact the availability and continuity of fuel, but different vegetation types also exhibit varying levels of flammability. To obtain land cover data, we utilized the Land Use and Vegetation Map of the state of Jalisco. This map was generated by the National Forestry Commission together with the Ministry of Environment and Territorial Development (Conafor and Semadat, 2020), utilizing satellite imagery captured by Landsat 8 from the year 2016; it is available in a vector format at a scale of 1:75,000 and offers detailed information on 19 distinct classes of land use and vegetation (see Figure S2). To enhance model interpretability (Díaz-Avalos et al., 2001) and reduce complexity, we grouped vegetation types with similar fuel characteristics, following established classifications used in previous studies exploring spatio-temporal wildfire variability at a national scale in Mexico (Rodríguez Trejo, 2008; Corona-Núñez et al., 2020; Montoya et al., 2023). The final land cover

Table 1
Landcover classes employed in the analysis, derived from the Land Use and Vegetation Map of the state of Jalisco. The classification was based on fuel characteristics and follows established criteria used in previous wildfire studies.

Land Cover Class	Land Cover Type
1	Pine-oak forests
2	Tropical dry forests
3	Tropical evergreen forests
4	Arid and semi-arid scrublands
5	Natural grasslands
6	Wetlands
7	Agricultural lands and Induced grasslands
8	Urban zones or no vegetation

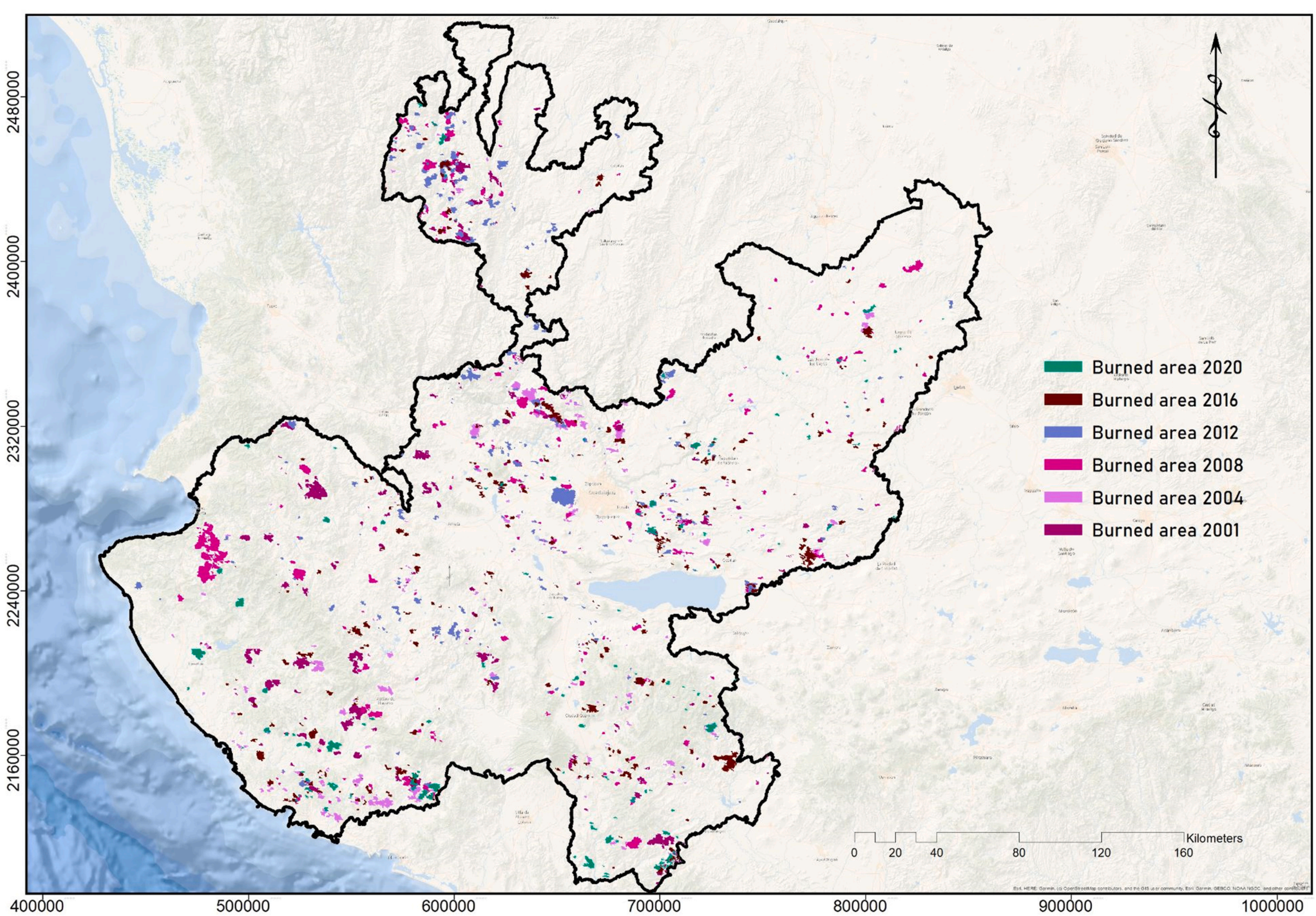

Fig. 1. Largest fire episodes detected for select years during the study period in the state of Jalisco. Burned area polygons illustrate individual fire events, highlighting the overlap of multiple fires in those years. Color-coded distinctions emphasize the cumulative impact of fires over time.

categories selected for the study are presented in Table 1, and the reclassified land cover map illustrating these categories is available in Figure S3. Refer to Table S1 for a more comprehensive overview of the key attributes associated with different land cover types in the study area.

2.3.2. Topography

Topographic factors, including elevation, aspect, and slope, play a significant role in shaping the type, amount, arrangement, and continuity of fuels by indirectly influencing the distribution of vegetation (Gill and Taylor, 2009; Falk et al., 2011). Moreover, topography directly influences fire by affecting its local behavior. To incorporate these factors into our analysis, we obtained elevation data from a Digital Elevation Map available for the study area, provided in a raster format with a 15-meter resolution (INEGI, 2012). Utilizing a GIS, we derived slope and aspect maps from the elevation raster, maintaining the same resolution. Slope refers to the steepness or incline of a surface and is expressed in degrees, while aspect indicates the orientation of the slope, measured in degrees from 0 to 360 in a clockwise direction; specifically, 0 degrees corresponds to a north-facing slope, 90 degrees to an east-facing slope, 180 degrees to a south-facing slope, and 270 degrees to a west-facing slope (Serra et al., 2014b). To simplify model interpretation and avoid excessive coefficients, we categorized both variables, as shown in the supplementary section (Tables S2 and S3).

2.3.3. Human activities

Human activities are a primary ignition source that significantly affects wildfire occurrence worldwide. Due to limited information on specific wildfire causes, we employed proxies to incorporate the influence of human factors and capture the proximity to potential ignition sources. We generated a distance to roads and highways raster (human-caused fires tend to ignite in areas close to roads) by employing an Urban Roads and Highway Map of Jalisco (Inegi, 2011), available in a vector format at a 1:50,000 resolution. Similarly, we derived a distance to agricultural land raster from the previously produced land cover map; this variable holds particular relevance, as agricultural burns are frequently reported as one of the main causes of wildfires in the region (Semadet, 2021). These variables not only exhibit a correlation with human ignitions but are also likely associated with the demand for firefighting and suppression efforts.

2.3.4. Temperature, precipitation, and NDVI

We used remote sensing MOD11A1 product to obtain daily per-pixel Land Surface Temperature and Emissivity data at a 1-kilometer spatial resolution. To assess precipitation, we accessed the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), which incorporates daily 5-kilometer resolution satellite imagery and in-situ station observations (Funk et al., 2015). It is important to note that in this study, temperature and precipitation data reflect the weather conditions at the approximate time and location of wildfires rather than long-term climatic patterns; therefore, their primary impact is on the moisture content of fuel.

While weather indices that aggregate meteorological factors are often used in fire studies (e.g., Castel-Clavera et al., 2022), we opted for raw temperature and precipitation data to take advantage of its higher spatial and temporal resolution, which is critical given the variability in weather conditions across Jalisco. Many available indices are based on coarser-resolution data or rely on local weather station data (Villers-Ruiz et al., 2012), which is often sparse or incomplete across the study region; by using raw satellite weather variables, we were able to better capture local-scale variations and benefit from the extensive coverage that satellite data offers. Moreover, the use of precipitation and temperature data has been successfully applied in studies using INLA to model wildfire behavior (Natário et al., 2013; Díaz-Avalos et al., 2016).

The Normalized Difference Vegetation Index (NDVI) is a widely used index derived from satellite imagery that measures the health and density of vegetation. We included NDVI as a proxy for local fuel conditions, as it can help estimate the amount and distribution of vegetation biomass in an area. Higher NDVI values indicate denser vegetation and potentially higher fuel loads, which can influence fire behavior and intensity (Chuvieco et al., 2004). Conversely, low NDVI values are linked to heightened vegetation dryness and water stress, making such areas more susceptible to ignition. The NDVI dataset was acquired from the MOD13Q1 product, which provides a vegetation index value at a per-pixel basis, generated every 16 days at 250-meter spatial resolution (Didan, 2015)

To handle the dynamic nature of these three variables and obtain a more comprehensive representation of the data, we summarized daily produced information by computing the mean monthly pixel values for each geospatial dataset. This resulted in 12 raster files per year for each variable (temperature, precipitation, and NDVI), covering the period from 2001 to 2020.

2.4. Association between wildfires and environmental factors

To ensure consistency and comparability, we standardized the environmental data for analysis by processing it in a GIS. This process included converting all data to raster format, standardizing resolution to 250 m for spatial uniformity, and selecting an appropriate coordinate system for accurate georeferencing. The final maps are shown in Fig. 2.

It is worth noting that while most environmental covariates had a native spatial resolution of 250 m or higher, the temperature and precipitation data used in our study had a coarser resolution (refer to Section 2.3.4). To match the resolution of the remaining datasets, we applied a resampling process to the temperature and precipitation rasters, adjusting them to 250 m. Although this resampling did not enhance the intrinsic accuracy of these datasets, it allowed for spatial consistency across all variables.

To integrate wildfire data, we overlaid the burned area polygons onto the stacked layer of environmental rasters. Our aim was to capture the environmental variables at the location of centroids of each fire polygon, thereby extracting relevant pixel values from the raster data. For dynamic factors (temperature, precipitation, NDVI), we specifically selected the layers that matched the month and year of the recorded fire episode. This approach facilitated the association of environmental conditions with individual fire incident attributes.

It is worth mentioning that fire events associated with agricultural land and induced grasslands pixels were classified as agricultural burns, while events occurring in any other type of vegetation cover, such as grassland, forest, or scrubland, were considered wildfires.

In our analysis, we predominantly focus on wildfires, with a selective approach to fires occurring in agricultural lands and induced grasslands. Specifically, in the initial stages of our exploratory analysis aimed at understanding general fire patterns across the state of Jalisco, we have included agricultural burns to provide a comprehensive overview of fire activity. However, in the detailed covariate-wildfire association analysis and subsequent modeling processes, we concentrate solely on wildfires. This approach ensures that our modeling accurately captures the dynamics specific to uncontrolled natural fires within the study area, while still acknowledging the broader context of fire occurrence in the region.

2.5. Statistical methodology

To gain insights into the spatial distribution of the area burned by wildfires and identify the relevant factors contributing to the variation in fire size within our study site, we employed statistical models utilizing a Bayesian probabilistic approach. By associating wildfires with their spatial coordinates (longitude and latitude of their centroid), along with variables such as size and ignition time, we were able to identify them through a spatio-temporal stochastic process (Serra et al., 2014a). In this approach, we treated observed patterns of fire occurrences as realizations of a spatio-temporal point process, where points correspond to

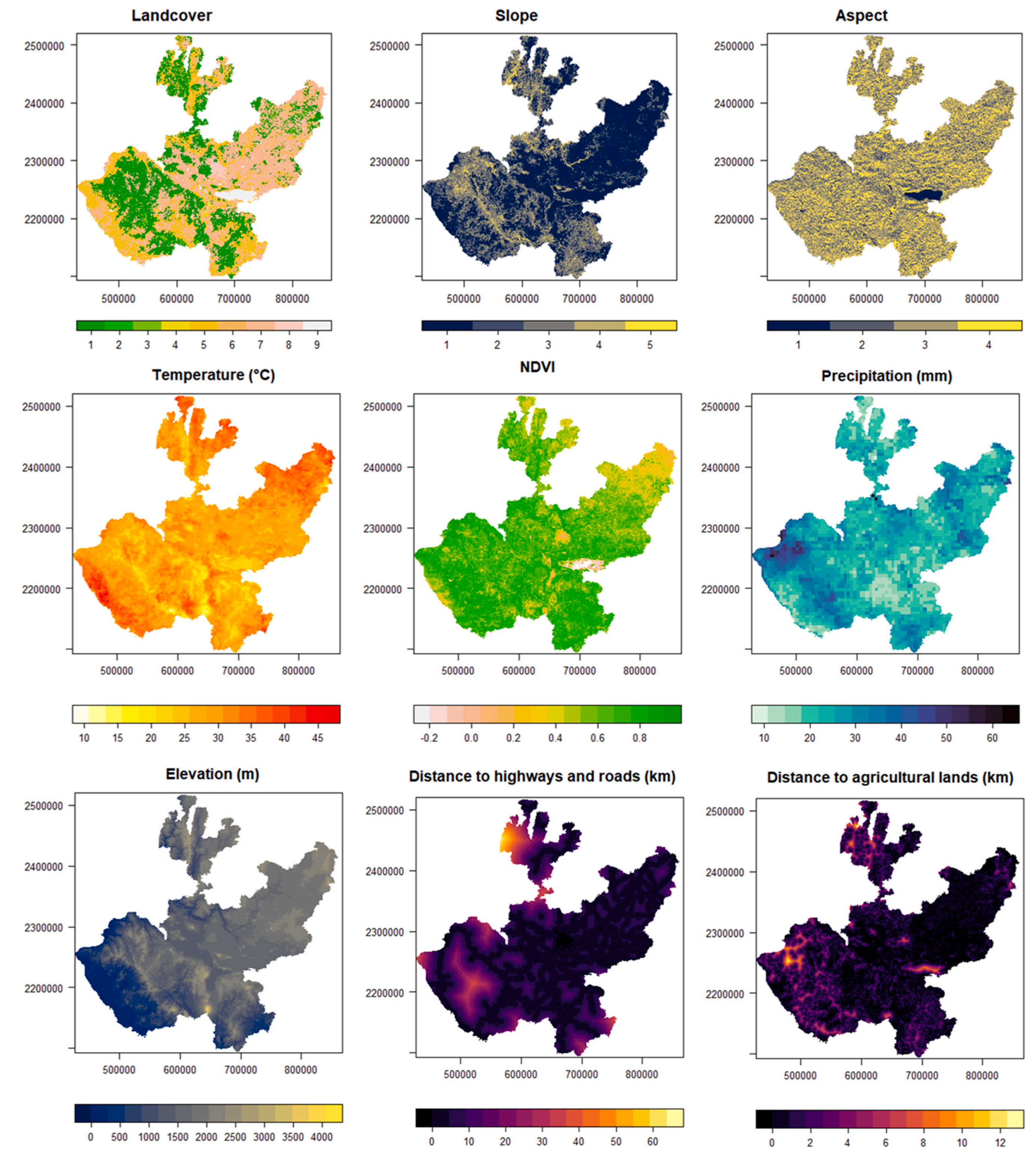

Fig. 2. Environmental wildfire-influencing factors in the state of Jalisco, Mexico. The maps depict six continuous variables (NDVI, elevation, precipitation, temperature, distance to roads, and distance to agricultural lands) and three categorical variables (land use, slope, and aspect) that were incorporated into the analysis. For illustrative purposes, the maps for temperature, precipitation, and NDVI represent aggregated mean values for a randomly selected month and year. The land cover map is coded as follows: 1-Pine-Oak Forest, 2-Scrublands, 3-Tropical Evergreen Forests, 4-Wetlands, 5-tropical dry forests, 6-Grasslands, 7-Agricultural lands, 8- Urban or no vegetation, 9-Water Bodies. The slope map is coded as follows: 1-Gentle, 2-Moderate, 3-Moderately Steep, 4-Steep, 5-Very Steep. The aspect map is coded as follows: 1-North, 2-East, 3-South, 4-West.

locations and times of ignition of a fire, and the burnt area is used as a mark for the points (Serra et al., 2014a; Díaz-Avalos et al., 2016; Pimont et al., 2020). Considering that the size of a wildfire is strongly associated with spatially varying factors such as vegetation, topography, weather, and ignition sources, which in turn influence the type, amount, dryness, and continuity of fuels (McKenzie et al., 2011), we incorporated these factors as covariates in the modeling process.

We modeled the burned area in the state of Jalisco using a hierarchical framework (Díaz-Avalos et al., 2016), treating wildfire size as a strictly positive random variable. Accordingly, we employed a Gamma distribution to capture the variability in wildfire size. The model's log-linear structure incorporates a Gaussian spatial error term to account for spatial autocorrelation in the data:

$$y_i|x_i,\beta, \quad u_i,\theta \sim Gamma(a_i,b_i); E[y_i] = \mu_i = \frac{a_i}{b_i}; \mathrm{var}(y_i) \quad = \quad \frac{a_i}{b^2{}_i} \tag{1}$$

$$\log(\mu_i) = \quad \beta_0 + \quad \sum_{j=1}^{J} \beta_j m_{ij} + \sum_{l=1}^{L} f_l(m_{il}) + u_i \tag{2}$$

$$u_i \quad \sim GMRF\left(0, \quad \lambda^{-1}\Sigma \quad \right) \tag{3}$$

Where y_i is the observed final size of the i-th wildfire at site x_i, modeled as a random variable following a Gamma distribution (Fig. 3) with shape parameter a_i and rate parameter b_i.

The logarithm of the mean wildfire size (μ_i) is linked to a linear combination of parameters. Specifically, we have β_0 as a random intercept and $\beta = (\beta_1, \quad \ldots \quad, \quad \beta \quad _J)$ as a vector of unknown coefficients quantifying the linear effect of covariates (see Fig. 2 for details on covariates) on the response variable. Additionally, we incorporate a collection of functions denoted as $f = \{f_1(\bullet), \quad \ldots \quad, \quad f_L(\bullet)\}$. These functions can assume various forms, such as smooth and nonlinear effects of covariates, allowing us to account for spatial correlation, temporal effects and the randomization of indexed wildfire events.

Finally, u_i represents the Latent Gaussian Markov Random Field (GMRF), which accounts for spatial dependencies among wildfire events. It follows a GMRF distribution with zero mean and precision parameter $\lambda^{-1}\Sigma$.

2.6. Model fitting and assessment

2.6.1. INLA and SPDE framework

For model fitting, we used the Integrated Nested Laplace Approximation (INLA) (Rue et al., 2009). INLA can handle large datasets by employing sophisticated hierarchical structures and has proven to be a computationally efficient alternative to Markov Chain Monte Carlo (MCMC) (Díaz-Avalos et al., 2016; Martino, Riebler, 2019). It allows nonlinear responses to explanatory variables to be estimated through flexible Gaussian prior distributions for spline functions in combination with spatial models (Pimont et al., 2020).

Because wildfires often exhibit spatial dependence or correlation (e.g., wildfires can modify the landscape in ways that affect future fire behavior), we incorporated a discrete approximation based on Stochastic Partial Differential Equation (SPDE), which provides a framework to model spatial dependence by describing the underlying continuous spatial process and its behavior over space (Lindgren et al., 2011). SPDE consists in representing a continuous spatial process, such a Gaussian field (GF), using a discretely indexed spatial random process, such as a Gaussian Markov Random Field (GMRF) (Chaudhuri et al., 2023a, Chaudhuri et al., 2023b).

To estimate the joint posterior distribution, we applied the INLA-SPDE method proposed by Lindgren et al. (2011). The SPDE framework represents a continuous spatial process via a discretized GMRF, with the spatial process U(.) modelled as a zero-mean Gaussian process with a Matérn covariance function (Matérn, 1960):

$$\mathrm{Cov}\left(U(x_i), U(x_j)\right) = \frac{\sigma^2}{2^{\nu-1}\Gamma(\nu)}\left(\kappa \parallel x_i - x_j \parallel\right)^{\nu} \quad K_{\nu}\left(\kappa \parallel x_i - x_j \parallel\right) \tag{4}$$

where $K\nu(.)$ represents the modified Bessel function of the second kind, Γ is the Gamma function, and $\nu > 0$ and $\kappa > 0$ are the smoothness and scaling parameters, respectively. The INLA approach constructs a Matérn SPDE model characterized by a spatial range r and a standard deviation parameter σ.

The parameterized model is formulated as:

$$\left(\kappa^2 - \Delta\right)^{(\alpha/2)}(\tau S) = Won\mathbb{R}^d \tag{5}$$

where $\Delta = \sum_{i=1}^{d} \frac{\partial^2}{\partial x_i^2}$ is the Laplacian operator, $\alpha = (\nu + d/2)$ is the smoothness parameter, τ is inversely proportional to σ, W is Gaussian

Fig. 3. Frequency histogram of wildfire size in the state of Jalisco during the period 2001–2020. The asymmetric shape of the gamma distribution is a characteristic feature of the burned area caused by wildfires (Alvarado, 1992). It is characterized by a high percentage of small and medium-sized fires, with a low number of larger fires at the tail end of the distribution.

white noise and $\kappa > 0$ is the scale parameter associated with the spatial range r. The range r is defined as the distance at which the spatial correlation becomes negligible, given by $r = \sqrt{8\nu}/\kappa$ for each ν, where r is the distance at which the spatial correlation is approximately 0.1. Note that we have $d = 2$ for a two-dimensional process, and we fix $\nu = 1$, so that $\alpha = 2$ in this case (Blangiardo and Cameletti, 2015).

In this study, we used the default priors provided by INLA-SPDE. Specifically, for the Gamma distribution used to model wildfire sizes, we applied the default Gamma prior with shape $a = 1$ and rate $b = 0.00005$, providing weakly informative priors for the precision parameters. Similarly, for the spatial random effects modeled using a GMRF, we used the default log-Gamma prior for the precision with $a = 1$ and $b = 0.00005$. The default prior distributions for all parameters in R-INLA were selected based on commonly used priors in previous studies (Martins et al., 2013; Blangiardo and Cameletti, 2015; Rue et al., 2017; Moraga et al., 2021). We tested alternative prior specifications and consistently obtained similar results, indicating that our findings are robust.

The INLA-SPDE and modeling approach were implemented in the R software package 'INLA' (R Core Team, 2021; Rue et al., 2009)

2.6.2. Mesh construction

The INLA-SPDE requires a triangulation or mesh structure to interpolate discrete event locations for estimating a continuous spatial process (Rue et al., 2017). In our case, we used the centroid coordinates of each wildfire as the target locations to construct the mesh, with the boundary defined by the natural limits of Jalisco. This ensured that the mesh followed the actual geographical limits of the study area.

A two-dimensional triangulation was applied, with varying mesh resolutions to optimize both spatial accuracy and computational efficiency. A finer mesh was employed in the core areas to capture greater detail, while a coarser mesh was used toward the boundary to reduce computational load without sacrificing overall precision. Additionally, the offset parameter was adjusted to extend the mesh 0.2–0.4 units from the boundary, minimizing boundary effects and preventing extrapolation beyond the study area. This approach effectively balances the need for accuracy with computational efficiency.

The triangulation of the study site utilized for estimation is illustrated in the results section (see Fig. 7).

2.6.3. Temporal and random effects

In addition to the spatial term, a temporal effect was modeled using a random walk of order one, which captures temporal correlation by allowing fire occurrences and sizes to vary over time (Serra et al., 2014b). We also included a random effect, which was applied to indexed wildfire events to capture unexplained variability not associated with spatial or temporal dimensions. This randomization introduces variability into the data that accounts for unknown factors influencing wildfire size, providing a more comprehensive model (Chaudhuri et al., 2023a)

Note that model [2] assumes spatial and temporal separability, which simplifies the modeling process by reducing complexity while maintaining interpretability. This assumption implies that the spatial distribution of wildfire sizes retains a consistent pattern over the years, with the overall scale of the process varying over time. In other words, the proportion of expected wildfire sizes between two locations, x_i and x_j, remains constant across different years, as both are scaled by the same time-varying factor.This approach offers several advantages. First, it leads to a more parsimonious model, which is crucial given the time resolution used in this study. Second, the separable model allows for easier interpretation, particularly when the primary objective is to assess the significance of environmental and human factors influencing the spatial distribution of wildfire sizes. While this assumption may limit the model's ability to capture intricate space-time interactions, it is a practical and effective choice in cases like ours, where screening for key drivers of wildfire activity is the primary goal.

2.6.4. Model selection and assessment

Model components were trained with data from 2001 to 2017 (training sample), while the years 2018–2020 were used for evaluating its predictive performance (validation sample). To find the optimal model and avoid overfitting (Xi, 2019), we estimated several models, starting with the simplest ones that included only one covariate and gradually progressing to a complete model encompassing all the covariates plus the spatial term (Table 2). For model selection, we employed the Deviance Information Criterion (DIC) and the Widely Applicable Information Criterion (WAIC), which are generalizations of the well-known Akaike Information Criterion (AIC) for Bayesian models (Pimont et al., 2020). Additionally, we calculated the Coefficient of Determination (R^2) and the Root Mean Squared Error (RMSE). Among these criteria, WAIC was given priority as it is known to better capture the posterior uncertainty in model predictions compared to DIC, which can occasionally favor overfitting (Vehtari et al., 2017; Pimont et al., 2020).

3. Results

3.1. Fire occurrence and burned area across the State of Jalisco

The frequency of fires in each year of the study period is illustrated in Fig. 4. Wildfires occurred at an average rate of 192 events per year, while agricultural burns had an average of 94 events annually. Although wildfires were more frequent than agricultural burns, both exhibited high interannual variability. In either scenario, the years 2005, 2011, and 2017 stood out as the most affected, whereas 2014 and 2015 experienced below-average number of fire episodes.

Over the study period, a total of 1434,831 ha were affected by wildfires, amounting to approximately 30 % of the forest vegetation cover in Jalisco. These results indicate that Jalisco is among the Mexican states most affected by fire, as supported by findings from Conafor (2023). On an annual basis, wildfires consumed an average of 71, 742 ha, with an average size of 372 ha per event. In contrast, agricultural burns were smaller in scale, averaging 218 ha per event, and accounted for only 22 % of the total estimated burned area.

Large-scale events were defined as fires with a final size exceeding 2000 ha. Throughout the study period, a total of 137 wildfires and 14 agricultural burns of such magnitude were documented. Agricultural burns of this scale are relatively uncommon, suggesting that these ignitions may have originated from agricultural lands that unintentionally or deliberately spread into forest vegetation, potentially for the purpose

Table 2
List of different models fitted to the wildfire burned area data in the state of Jalisco during the period 2001–2020. The term 'spatial' refers to the incorporation of the SPDE approach, which accounts for the spatial correlation among wildfire sizes. The term 'temporal' indicates the inclusion of a random walk of order one, capturing the temporal effects on wildfire size. The term 'random' denotes a variability component applied to the indexed wildfire events, which introduces variability unrelated to the spatial or temporal dimensions and accounts for additional unexplained variation in wildfire size. Finally, the term 'covariates' represents the environmental factors influencing wildfire patterns, which were previously linked to each fire event.

Model	Terms
M1 a M9	Model for each covariate
M10	All covariates
M11	Spatial effect
M12	Temporal effect
M13	Covariates + Random effect
M14	Covariates + Spatial effect
M15	Covariates + Temporal effect
M16	Covariables + Temporal + Spatial effect
M17	Covariables + Temporal + Spatial + Random effect

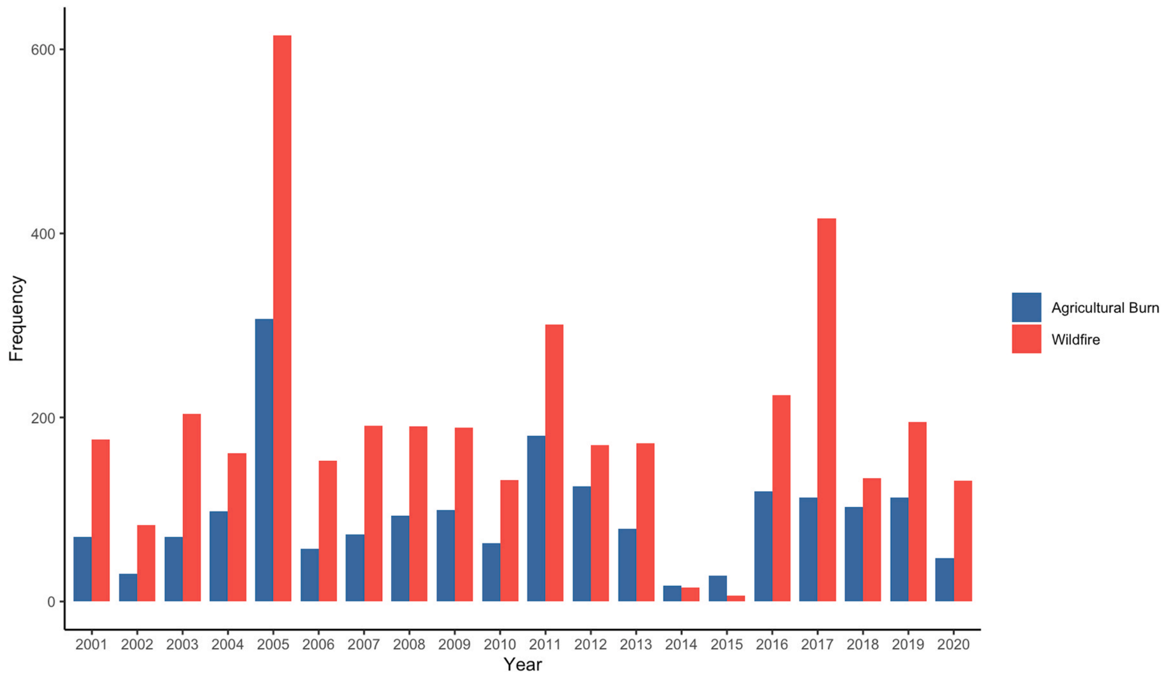

Fig. 4. Annual wildfire and agricultural burning occurrence in the state of Jalisco during the period 2001–2020.

of land cover change (Balcázar, 2011).

Our analysis also revealed distinct wildfire behavior patterns across various vegetation covers within the state (see Table 3). Pine-oak forests exhibited the highest incidence of wildfire occurrences, accounting for 67.3 % of all recorded events, and presented the largest extent of burned area, encompassing 78.4 % of the total. Furthermore, out of the 137 large-scale wildfires documented during the study period, a significant majority of 121 (88.32 %) originated in pine-oak forests. Notably, these forests also experienced the largest individual events, with an average wildfire size of 433.62 ha.

Tropical dry forests are ecosystems characterized by marked seasonality, with distinct wet and dry seasons (Sutomo and van Etten, 2023). In our study area, these ecosystems emerged as the second most affected vegetation type, accounting for 30.7 % of all recorded wildfire events and 20.3 % of the total burned area. Although most wildfires within these forests were small to medium in scale, extending less than 400 ha (83.05 % of cases), we documented 15 large-scale episodes.

Scrublands experienced the second-largest average wildfire size, at 270.8 ha per event. Conversely, Grasslands recorded a slightly lower average size of 201 ha per event but notably hosted one large-scale wildfire. Combined, these two vegetation covers accounted for approximately 2 % of the total number of fire occurrences and the overall burned area.

Lastly, tropical evergreen forests and wetlands exhibited the lowest levels of wildfire activity, accounting for less than 0.5 % of both wildfire occurrences and the total burned area throughout the study period.

Fig. 5 illustrates the annual proportion of burned area relative to the total surface area of each vegetation cover in the state of Jalisco. The boxplot reveals that pine-oak forests experience the highest average annual burn percentage, with 2.41 % of their total area affected by wildfires each year. This is followed by tropical dry forests, with an average of 0.74 %, and agricultural lands (including induced grasslands) at 0.70 %. Scrublands and natural grasslands show a lower average percentage, with 0.43 % and 0.39 % respectively, while tropical evergreen forests and wetlands register the least proportion of burned area annually, at 0.11 % and 0.002 %, respectively.

It is important to emphasize that these percentages may represent areas subjected to repeated burning; hence, they do not imply that new, previously unburned sections of vegetation are affected each year.

Table 3
Wildfire behavior across different vegetation covers in the state of Jalisco. These results highlight the differentiated impact and frequency of wildfires, underscoring the variable susceptibility and fire dynamics of each vegetation type during the study period.

Vegetation Type	Total Fire Occurrence	Total Burned Area (ha)	Average Size per Event (ha)	Fire Events > 2.000 ha
Pine-Oak Forest	2595	1,125,231.36	433.62	121
Scrubland	32	8665.40	270.79	0
Tropical Dry Forest	1180	291,160.68	246.75	15
Tropical Evergreen Forest	6	1130.34	188.39	0
Natural Grassland	43	8643.53	201.01	1
Wetland	2	11.66	5.83	0
Agricultural Land	1885	412,250.69	218.70	14

3.2. Covariate values associated with wildfire occurrence

Fig. 6 shows the frequency histogram for the covariate values associated with wildfire occurrences. The color code indicates the corresponding vegetation cover where the wildfire event was recorded. It is important to note that the actual distribution of burned pixels may differ, as wildfires can spread into areas with distinct covariate values than those of the ignition location (Díaz-Avalos et al., 2016).

Elevation values associated with wildfire occurrence exhibited a distinct grouping corresponding to the elevation ranges where different vegetation types are typically established (Fig. 6-A). For instance, wildfires originating in pine-oak forests were most frequently observed at elevations ranging from 1500 to 2500 m, which coincides with the prevalent location of these forests within the study site (Jardel-Peláez et al., 2012). In contrast, wildfires in tropical dry forests spanned an elevation range from 0 to 2000 m; this wider range can be attributed to the presence of low and medium tropical dry forests, two distinct

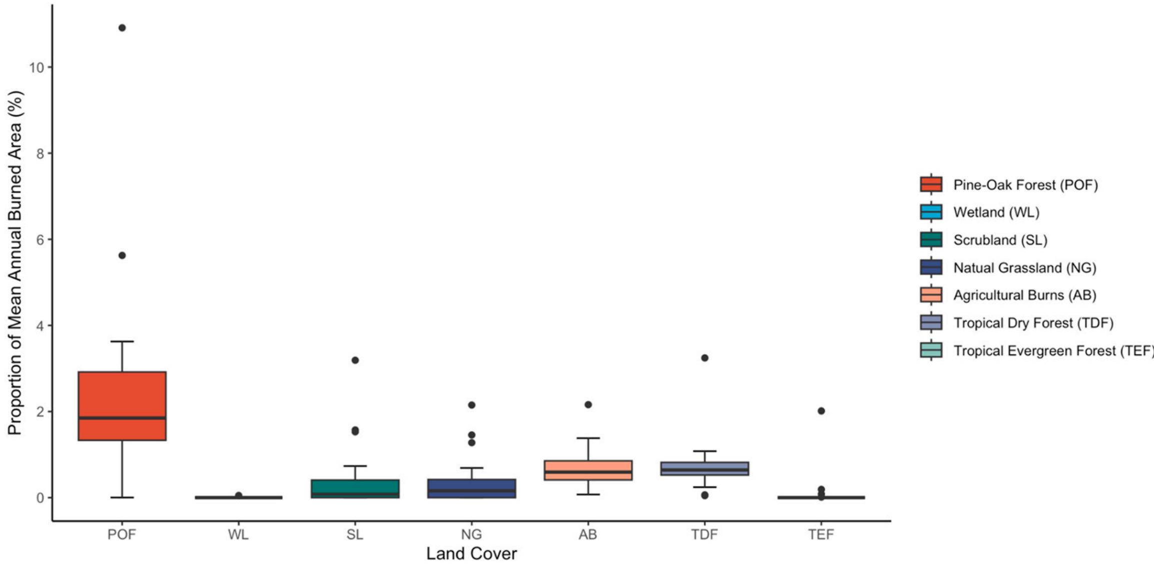

Fig. 5. Boxplot of the mean annual burned area as a percentage of total vegetation cover. The median is marked by the line within each box, the interquartile range by the box itself, and outliers by the dots. This visualization provides a comparative perspective on the relative impact of fires across different vegetation covers in Jalisco, indicating not only average burn proportions but also the variability within each vegetation type. Note that percentages may reflect areas that have experienced repeated burning over the study period. Total coverage for each vegetation class was derived from the previous Land Use and Vegetation Map of the state of Jalisco.

vegetation communities that combined, encompass a broader altitudinal distribution (Pennington et al., 2009). Similarly, scrublands and grasslands in Mexico are commonly found at medium altitudes, aligning with the elevation values associated with ignitions in these ecosystems (Challenger, Soberón, 2008).

The remaining covariates showed a similar distribution pattern across all vegetation covers, suggesting a constant relationship with wildfire occurrence regardless of the ecosystem type. In other words, these environmental factors seem to exert a comparable influence on wildfire incidence across various vegetation covers within the state of Jalisco.

The frequency histogram of NDVI (Fig. 6-B) reveals that wildfires were more prevalent in values falling within the lower range of the index interval. Lower NDVI values typically indicate reduced photosynthetic activity and heightened water stress, both of which contribute to drier fuel conditions that are more prone to ignition. Additionally, we observed a strong association between wildfire occurrences and precipitation values near zero (Fig. 6-C). Conversely, wildfire frequency exhibited a positive correlation with temperature, with the highest incidence observed during periods of elevated temperatures (Fig. 6-D).

Fig. 6-E illustrates the distribution of wildfires across various slope categories. Notably, we found a higher frequency of wildfires in moderate (10° to 15°) and moderately steep (15° to 25°) terrains. In Fig. 6-F, we observe that wildfires were more frequent in south and east-facing slopes. At this latitude, southerly and easterly-facing slopes generally receive more direct sunlight and higher solar radiation throughout the day (Méndez-Toribio et al., 2016), which could translate into dryer environmental conditions.

Fig. 6-G and Fig. 6-H demonstrate a notable declining trend in the occurrence of wildfires as the distance to the nearest road and agricultural land increases. This pattern suggests that roads and agricultural areas, which are often associated with human activities such as discarded items like cigarettes, intentional burns, or agricultural practices, could act as potential sources of fire ignition.

3.3. Wildfire size modeling

Fig. 7 illustrates the triangulation employed across the state of Jalisco for the period 2001–2020, with finer spatial resolution within state boundaries to accurately capture wildfire locations, depicted as red dots. This mesh forms the basis for interpolating discrete event locations and estimating a continuous spatial process, crucial for our wildfire size modeling. The mesh configuration ensured alignment between the centroids of wildfire occurrences and the vertices of the triangulation, facilitating an accurate spatial representation for subsequent modeling efforts.

Following the establishment of the spatial framework, we evaluated the performance of various models fitted to the wildfire size data. The information criteria for the five best models fitted to the wildfire size data are reported in Table 4. The best-performing model based on the WAIC (Watanabe-Akaike Information Criterion) criterion was the full model (M19), which exhibited the lowest WAIC value. Additionally, Model M19 showed the smallest DIC (Deviance Information Criterion), an R^2 value closest to one, and the lowest error among all the models. Overall, our observations revealed a trend of improved model performance with increasing complexity, particularly when incorporating the spatial effect, implying a spatial association among the wildfires analyzed within the study site (Díaz-Avalos et al., 2016).

In our model development process, we systematically explored various combinations of covariates to simulate a variable selection process. Initially, we assessed models based on simple sets of covariates, and progressively introduced more sophisticated ones. To optimize the model, we also experimented with excluding specific environmental covariates from these configurations, aiming to evaluate the impact of simplification on model performance. However, this approach invariably led to increased values of WAIC and DIC, indicating a deterioration in model efficiency. This pattern suggested that the omission of any covariates, irrespective of their nature, compromised the model's ability to accurately reflect the complexities of wildfire dynamics, emphasizing the critical role of including a full spectrum of covariate information in the model fitting process.

In Table 5, we present the coefficient estimates for the significant covariates of model M19, our best-performing model. Each coefficient is displayed alongside its standard deviation, and statistical significance was assessed using extreme quantiles, indicating significance when these do not encompass zero.

Two land cover classes, wetlands and tropical deciduous forests, exhibited significant coefficients. In the context of categorical variables,

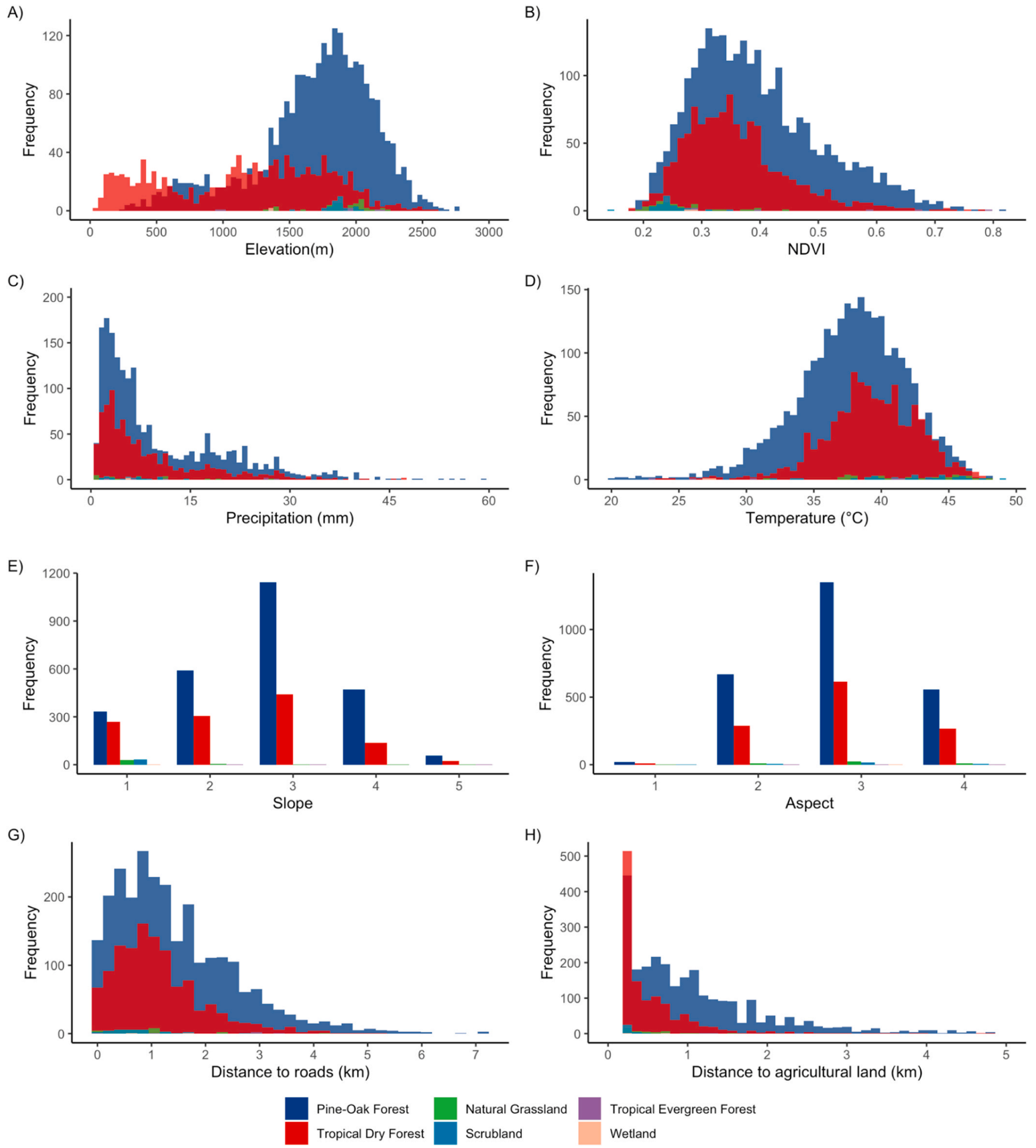

Fig. 6. Frequency histograms for the covariate values associated with wildfire occurrence in the state of Jalisco during the period 2001–2020, segmented by vegetation type. The color code for these histograms represents distinct vegetation types with recorded wildfire incidents: blue for pine-oak forests, red for tropical dry forests, green for natural grasslands, blue for scrublands, purple for tropical evergreen forests, and pink for wetlands. For categorical variables, slope is encoded as follows: 1-Gentle, 2-Moderate, 3-Moderately Steep, 4-Steep, 5-Very Steep; aspect is categorized as: 1-North, 2-East, 3-South, 4-West.

it is common to designate a specific category as the 'reference category' for coefficient interpretation. Consequently, the model intercept becomes the estimated effect for the dropped category, while the coefficients for the remaining categories represent deviations from its mean effect (Starkweather, 2018). As the reference category for land cover was pine-oak forests, the negative sign associated with both wetlands and tropical deciduous forests indicates that wildfires in these vegetation types tend to be smaller when compared to fires in pine-oak forests, which is consistent with previous findings (Table 3).

To interpret these coefficients, we exponentiated the values to express the expected fire size relative to pine-oak forests, the reference category. The exponentiated coefficient for wetlands indicates that the

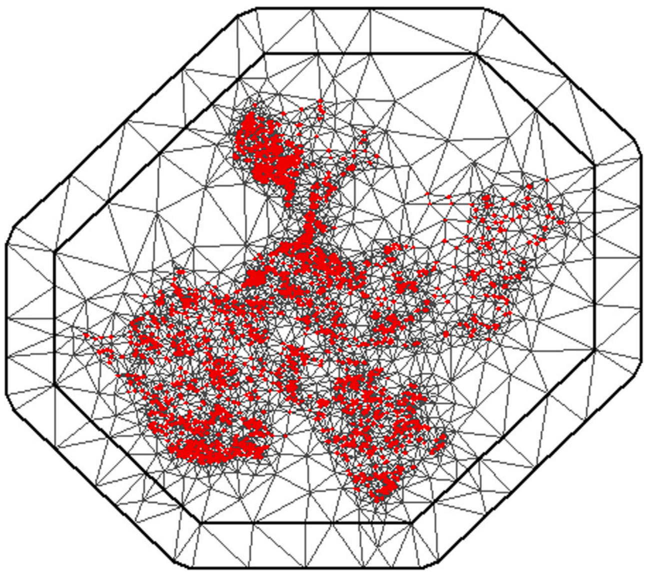

Fig. 7. Mesh configuration used in the INLA-SPDE method for the state of Jalisco, during the period 2001–2020. The triangulation provides finer spatial resolution within the state boundaries, while wider triangles cover the surrounding area. Red dots represent the locations of the wildfire's centroids, coinciding with triangle vertices.

Table 4
Information criteria for the five best models fitted to the wildfire size data in the state of Jalisco during the period 2001–2017. For detailed descriptions of the terms included in each model, please refer to the methodology section.

MODEL	TERMS	DIC	WAIC	R2	RMSE
M19	Covariates + Spatial + Temporal + Random	10535.24	11426.45	0.94	4.28
M18	Covariates + Spatial + Temporal	10566.28	11467.02	0.93	4.61
M16	Covariates + Spatial	10590.56	11475.13	0.93	4.58
M17	Covariates + Temporal	12932.90	13020.46	0.30	8.50
M12	Covariates	13063.83	13096.71	0.21	8.69

Table 5
Coefficient estimates for the significant covariate effects of model M19 fitted to the fire size data in the state of Jalisco during the period 2001–2017. Each coefficient is presented along with its standard deviation, and its statistical significance was assessed using extreme quantiles.

Covariates	Mean	Standard deviation	$q_{0.025}$	$q_{0.975}$
Intercept	−0.616	0.609	−1.830	0.583
Wetlands	−2.591	1.261	−5.068	−0.117
Tropical Dry Forest	−0.307	0.082	−0.467	−0.146
Easterly aspect	−0.715	0.285	−1.274	−0.156
Southerly aspect	−0.652	0.282	−1.204	−0.099
Westerly aspect	−0.743	0.285	−1.302	−0.185
Temperature	0.045	0.012	0.021	0.070
NDVI	0.997	0.443	0.128	1.866
Distance to road	0.249	0.038	0.175	0.323
Distance to agricultural land	0.124	0.056	0.014	0.235

expected fire size in these areas is approximately 7.49 % of that in pine-oak forests, highlighting a substantially smaller fire size. Similarly, the coefficient for tropical dry forests suggests that the expected fire size is 73.6 % of what would be expected in pine-oak forests, indicating that while fires in tropical dry forests are also smaller than those in pine-oak forests, they are considerably larger compared to wetlands. This comparison remarks the significantly higher susceptibility of pine-oak forests to larger wildfires, as opposed to the other vegetation types analyzed.

All aspect or hillside exposure coefficients demonstrated statistical significance. The negative coefficients associated with easterly, southerly, and westerly-facing slopes indicate a smaller expected burned area in these categories compared to the northerly aspect, which served as the reference category. Exponentiating these coefficients, they reveal that easterly slopes are expected to have 48.9 % of the burned area compared to northerly slopes, while southerly and westerly-facing slopes are expected to have 52.1 % and 47.5 %, respectively. This finding contrasts with the observed pattern of wildfire occurrence in Fig. 6-F, where most ignitions were associated with southerly and easterly-facing slopes.

Among the continuous variables, temperature, NDVI, distance to the nearest road, and distance to the nearest agricultural land showed statistically significant and positive coefficients. These findings suggest that as the values of these variables increase, so does the extent of burned area caused by wildfires. Notably, NDVI displayed the highest positive significant coefficient of the model (0.997), reflecting a strong correlation with fire size.

It is important to highlight that coefficient estimates for NDVI and the nearest distances to roads and agricultural land diverge from the observed patterns of wildfire occurrence. While lower NDVI values were associated with a higher number of ignitions (Fig. 6-B), larger wildfires tended to occur in areas characterized by higher NDVI values. Similarly, although ignitions were more frequent near roads or crop fields (as depicted in Fig. 6 G-H), the majority of these resulted in small or medium-sized wildfires; in contrast, the largest wildfires within the study site tended to ignite in remote regions, where firefighting efforts require more time and resources.

3.4. Model validation

Fig. 8 displays the residual plots derived from the validation sample. Overall, a strong correlation was found between the observed and predicted values. Across the analyzed years, the residual plots displayed a random dispersion of data points without any discernible trend or pattern. The residual points formed a consistent-width band around the identity line y=0, indicating a reliable fit for the burned area data.

Notably, in 2018 and 2020, the residuals showed symmetrical distribution around the origin. However, in 2019, there was a higher number of atypical points located above the identity line, suggesting a slight underestimation of wildfire size at specific locations and a larger prediction error. Model fitting results removing those extreme values showed that the outlying observations had little effect on the inferences about the covariate effects and that the changes in the goodness of fit statistics changed only slightly. Despite the changes in RMSE and AIC, the conclusions about the best model selected remained the same.

The higher error observed in 2019 can be attributed to the occurrence of larger wildfire events during that year. While the model effectively estimated the final extent of small and medium-sized fires, its predictability was lower for events of greater magnitude. Furthermore, the model's ability to accurately predict large-scale events was limited, as its burned area estimates per event did not exceed 3000 ha. Considering future research within the study area, it would be advisable to treat large-scale events separately from the rest of the wildfires and develop independent models specifically tailored to predict their behavior.

To further assess the model's performance, the distribution of observed versus estimated burned area values for each validation year is illustrated in the histograms of Figure S4 in the Supplementary Material. These histograms show a similar pattern where the best predictions were made for 2018, followed by 2020, and 2019, which experienced more fire activity than average.

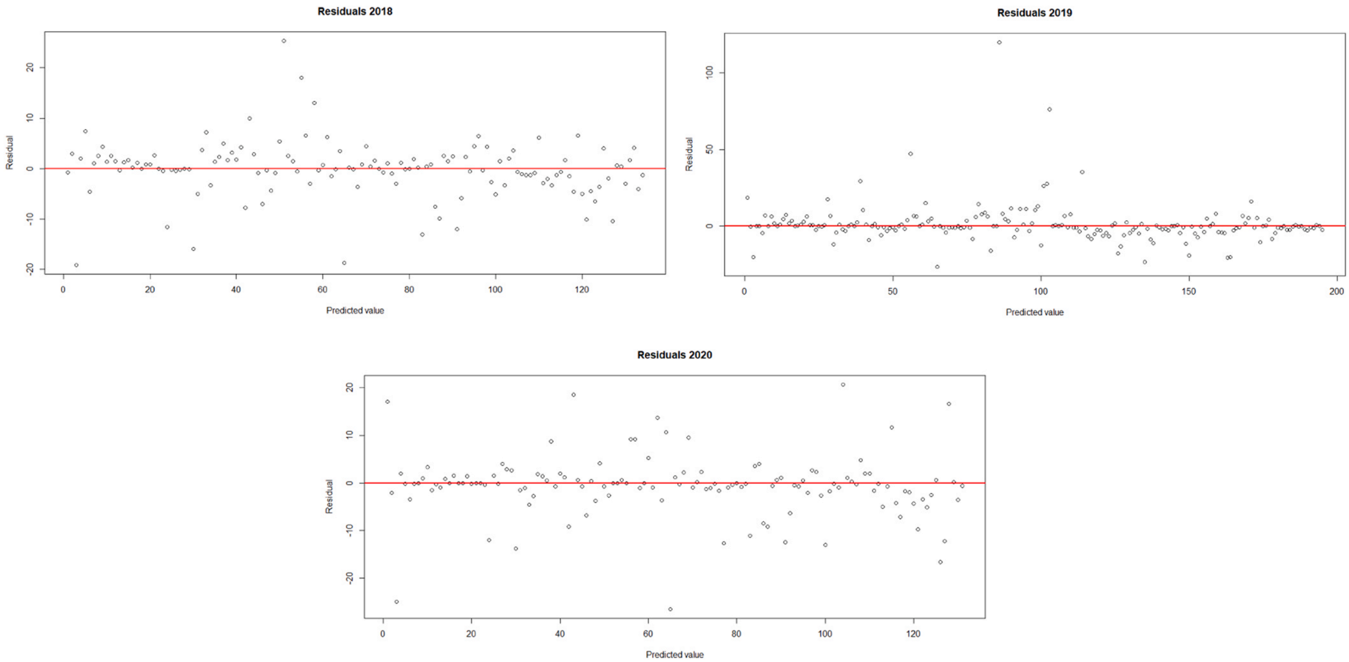

Fig. 8. Model residuals for the validation period 2018 (top-left), 2019 (top-right), and 2020 (bottom). The red line in each plot represents the identity line (y = 0), indicating where the estimated values align with the observed ones.

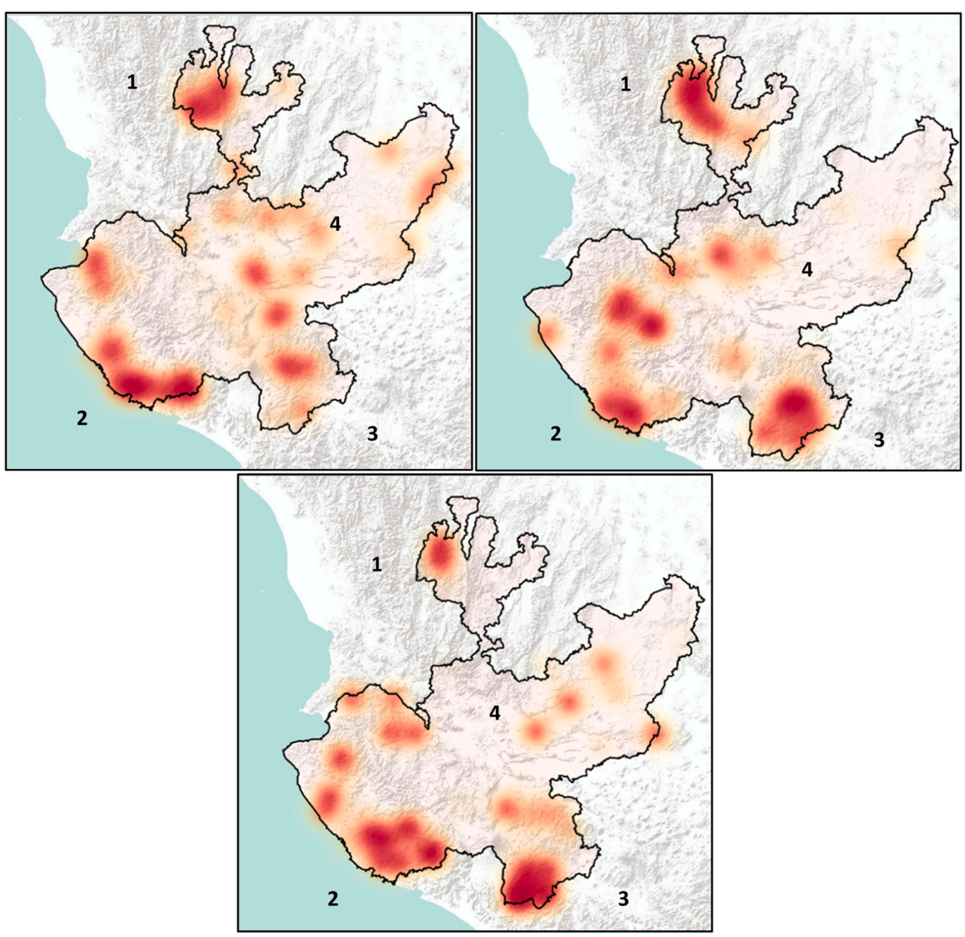

Fig. 9. Estimated burned area in the state of Jalisco for the years 2018 (top-left), 2019 (top-right), and 2020 (bottom). Regions exhibiting hotter shades of red indicate higher burned area values. The critical wildfire zones identified for the region are 1) the northern region 2) the southern coast 3) the southeast, and 4) the central region.

3.5. Spatial patterns of burned area in the State of Jalisco

To visually represent the spatial distribution of wildfires across the state of Jalisco, we focus on the period 2018–2020 (Fig. 9) as our model's validation phase. This period was specifically chosen to assess the predictive accuracy of our model outside the range of data used for its development. The maps highlight regions with the highest concentration of burned hectares, where burned area density reflects both the occurrence of a few large wildfires and the cumulative impact of numerous smaller ones, resulting in significant overall burned area coverage. Regions exhibiting hotter colors (represented by shades of red) denote areas with higher burned area values. To facilitate a complete evaluation of our model's predictive accuracy in relation to actual fire events, we refer readers to the Supplementary Material. There, we provide maps (Figure S5) of the actual burned area records for the validation years, allowing for a direct visual comparison between the model's estimates and real-world observations.

The spatial distribution of hotspots during the validation years reveals that certain regions within the state of Jalisco consistently exhibited a high density of large burned areas. These findings suggest the presence of areas where the risk of wildfires is persistently higher. Based on the state's administrative zonation provided by Ramírez et al. (2013), we identified four distinct fire-prone regions: the northern region, the southern coast, the southeast, and the central region, which includes densely populated areas such as Guadalajara, Zapopan and Tlajomulco (Fig. 9 A-C).

Within the scope of our spatial model analysis using the SPDE approach, we also estimated the nominal range, a parameter that characterizes the spatial correlation structure of a random field (Rue et al., 2009; Blangiardo and Cameletti, 2015). Our analysis revealed a nominal range of 3.736 km; this value suggests that there is a tendency for wildfires in our study site within approximately 3.736 km of each other to exhibit some level of correlation in terms of their sizes. In other words, wildfires within this distance are more likely to have a similar extent compared to those that are further apart.

4. Discussion

4.1. Wildfire dynamics and vegetation cover in Jalisco

Over the study period, wildfires occurred at a higher rate than agricultural burns, evidenced in both their frequency and total burned area. These findings are consistent with national-level reports, including those from the National Forestry Commission (Conafor, 2022) and Corona-Núñez (2020), which indicate a higher prevalence of wildfires compared to burns originating in agricultural lands. This alignment underscores the broader trend of wildfires as a primary concern for fire management and mitigation efforts in Mexico.

Significant interannual variability was noted in wildfire and agricultural burn occurrences, with 2005, 2011, and 2017 marking years of heightened activity and 2014 and 2015 seeing fewer incidents. This pattern aligns with Conagua (2023) data indicating intense droughts during the peak years and above-average rainfall in the quieter ones. Such variability emphasizes the influence of climatic extremes on fuel conditions and fire ignition rates in Jalisco.

Land cover influences the risk of wildfires by altering the spatial arrangement of fuels and interacting with weather conditions (Heyerdahl et al.,2001). In our study, different land cover types were found to be associated with varying levels of fire occurrence. Pine-oak forests emerged as the most fire-prone vegetation type, exhibiting both higher frequency and larger extent of wildfires. Furthermore, these forests registered the highest average annual percentage of burned area relative to their total extent within the study region. This observation is consistent with Montoya et al. (2023), who noted a comparable pattern at the national level, with pine-oak forests annually experiencing burns across an average of 2.7 % of their total area, suggesting a consistent wildfire behavior for this forest type across broader scales.

These findings also coincide with previous global studies indicating that wildfires are not uncommon in pine-oak forests, which maintain a fire regime characterized by frequent, low-intensity surface fires (Fule, Covington, 1996; Rodríguez-Trejo, Fulé, 2003; Heyerdahl and Alvarado, 2003; Jardel-Peláez et al., 2012). A substantial proportion of species in pine-oak forests have developed adaptations or resistance to wildfires, enabling them to not only survive but thrive and dominate in fire-prone environments (Keeley and Zedler, 1998).

However, the prevalence of large-scale fire events in these ecosystems, documented throughout our study, points to increased fire intensity, likely exacerbated by anthropogenic factors like fire suppression practices, which lead to fuel accumulation, and illegal burning activities, enhancing fire frequency and intensity. Additionally, the effects of climate change may further aggravate the severity of fires, disrupting established fire regimes (Jardel et al., 2006; Moreno-Ruiz et al., 2013; Bárcenas-Pazos et al., 2018). Such altered fire regimes in pine-oak forests could result in shifts in vegetation composition, biodiversity loss, and disruptions to key ecosystem processes (Gallardo-García et al., 2016), underscoring the critical need for understanding these dynamics to devise effective wildfire management and conservation approaches. For instance, controlled burning, recognized as a viable management strategy in fire-adapted ecosystems, allows for the maintenance of natural fire dynamics and prevents excessive fuel build-up (Jardel-Peláez et al., 2014).

Tropical dry forests ranked as the second most affected vegetation cover in Jalisco, which, along with pine-oak forests, accounted for approximately 98 % of the total area burned during the study period. This finding is in line with research conducted at the national level, which has consistently identified tropical dry forests as having a high incidence of wildfires (Rodriguez Trejo, 2008; Corona-Núñez et al., 2020; Montoya et al., 2023).

Globally, there is also evidence that wildfires are becoming more frequent and severe in many tropical dry forests, a trend documented in recent studies (Yin et al., 2020; Hartung et al., 2021; Corona-Núñez, Campo, 2023). Although these forests rank among the ecosystems most vulnerable to fire, their long-term response to frequent wildfires remains largely unknown (Hartung et al., 2021).

Rodriguez Trejo (2008) suggests that in Mexico, these forests' susceptibility to fire can be attributed to practices such as logging and intentional burning. Furthermore, the presence of secondary forests and human-induced disturbances, such as fragmentation, can intensify their vulnerability (Michael-Fuentes et al., 2010).

In the state of Jalisco, tropical dry forests are often located in proximity to agricultural land and serve as rangeland for cattle (Balcázar, 2011). Consequently, the use of fire to convert forest to farmland areas can be considered a contributing factor to the occurrence of wildfires in these ecosystems. Our analysis revealed that both tropical dry forests and agricultural land/induced grasslands experienced a similar annual burn percentage of their total surface area (approximately 0.7 %), suggesting a link between these land cover types. Additionally, the characteristic dry periods in these ecosystems can amplify their vulnerability to fire, especially under conditions of climatic uncertainty.

Despite most wildfires in tropical dry forests in Jalisco being smaller than 400 ha, their impacts can still be significant. These forests harbor fire-sensitive species that are not adapted to the presence of fire, making them more vulnerable to higher levels of damage and altered succession patterns (McKenzie et al., 2004; Jardel-Peláez et al., 2012).

4.2. Environmental factors driving wildfire behavior

4.2.1. Topography

The quantification of topographic effects on wildfire behavior posed a challenging task, primarily due to the intricate interplay of topography with various landscape elements.

In our exploratory analysis, elevation emerged as the only environmental factor where wildfire frequency exhibited variation based on the vegetation type associated with each fire event. This variation underscores elevation's important role in delineating the range of different vegetation types and, by extension, influencing wildfire distribution across elevational gradients.

Despite this, the size of wildfires did not exhibit a significant correlation with elevation in our model, diverging from recent findings that report elevation significantly affecting both the frequency and intensity of wildfires (Mansoor et al., 2022; Alizadeh et al., 2023). This suggests that the influence of elevation on wildfire behavior in Jalisco may be more complex, primarily exerting its impact indirectly by shaping the establishment and distribution of vegetation communities. This in turn, influences the availability and characteristics of fuel loads, affecting wildfire risk and behavior.

Our analysis indicated that moderate and moderately steep terrains exhibit a higher frequency of wildfires, though significant activity was also noted in the gentler topographies of tropical dry forests. Slope inclination directly facilitates fire spread by enhancing radiative heat transfer (Rothermel, 1983) and increasing both the rate of spread and fire intensity (Falk et al., 2011). Additionally, slope affects fire ignition indirectly by altering fuel moisture and density (Holden et al., 2009).

The decrease in fire activity within steep and very steep terrains observed in our study may stem from their relative inaccessibility compared to gentler areas, which favor denser road networks and are more habitable (Bountzouklis et al., 2021). This accessibility makes gentle to moderately sloped areas more susceptible to anthropogenic ignition sources, such as agriculture and intentional burning, thus elevating wildfire occurrence rates in these terrains (Balcázar, 2011).

On the other hand, our model did not identify a significant relationship between slope and wildfire size. Previous studies, such as the work by Parks et al. (2012), have reported that the influence of slope on wildfires could range from negligible to highly significant, depending on the specific characteristics of the study area. McKenzie et al. (2006) further noted that topography, particularly in rugged landscapes, plays a more critical role in shaping fire regimes than in areas of milder relief. Much like with elevation, the apparent lack of slope's direct impact on wildfire patterns in our study might be explained by the nuanced, indirect effects of landscape features on fire dynamics. Factors such as fuel availability, moisture, and continuity vary with slope inclination, potentially masking slope's direct influence on fire spread. Moreover, the scale of our analysis may limit our ability to accurately assess the localized effects of slope on specific fire events.

The complex role of topography in determining fire occurrence and size was further evidenced by our exploration of the effects of aspect on wildfire patterns. During the exploratory phase, it was noted that wildfires occurred more frequently on south and east-facing slopes. In the northern hemisphere, southerly and easterly-facing slopes generally receive more direct sunlight and higher solar radiation throughout the day (Méndez-Toribio et al., 2016). This increased sun exposure leads to higher temperatures, drier conditions, and greater evaporation rates, creating a more favorable environment for fire ignition and spread (Westerling et al., 2006; Díaz-Avalos et al., 2016).

Following this logic, it was anticipated that wildfires would be larger on southerly and easterly slopes. Surprisingly, our model's significant coefficients indicated that northerly slopes were associated with the most extensive wildfires in our study area. This apparent contradiction could stem from several factors: a) the less frequent ignition events on north-facing slopes might allow for more fuel accumulation, increasing the potential for larger fires; b) existing research on aspect and wildfire behavior primarily focuses on northern latitudes, with limited insights into subtropical climates like those in our study area; c) the relatively scarce presence of northerly slopes in Jalisco may lead to a data imbalance, affecting model precision (Agresti, Caffo, 2002). Furthermore, the interconnected nature of topographic features such as slope, elevation, and aspect adds another layer of complexity to their relationship with wildfire dynamics. Specifically, aspect's influence is heavily modulated by slope; in gentle terrain, solar energy input does not vary significantly across space, suggesting that gentle northerly slopes could receive nearly as much solar energy as southerly ones (Heyerdahl et al., 2001).

Overall, these observations suggest that the intricate ways in which topography affects wildfire occurrence and size—and its interaction with other landscape characteristics—were not fully captured by our modeling approach.

4.2.2. *Temperature and precipitation*

In our exploratory analysis, we observed a strong association between wildfire frequency and precipitation values near zero, irrespective of the originating vegetation cover. It is well established in the literature (e.g. Littell et al., 2009; Holden et al., 2018; Neger et al., 2022) that lack of precipitation or prolonged dry periods can lead to drought conditions, which significantly increase the risk of wildfires.

Conversely, our analysis found that wildfire frequency positively correlates with temperature, demonstrating the highest occurrences during periods of elevated temperatures. This observation was further supported by significant model coefficients indicating a direct relationship between temperature and the size of fires. The positive correlation between temperature and both the frequency and magnitude of wildfires can be attributed to higher temperatures' role in accelerating vegetation drying, thereby increasing fuel availability for fire propagation (Donat et al., 2013).

Temperature's crucial role in estimating wildfire dynamics has been consistently supported by previous research (Flanningan et al., 2009; Yang et al., 2014; Castel-Clavera et al., 2022), and it is widely recognized as a key driver of heightened wildfire activity (Westerling, 2016; Abatzoglou et al., 2019; Gutierrez et al., 2021). Temperature as a critical driver of wildfire behavior is particularly relevant in the context of climate change. One of the most significant consequences of climate change is global warming, resulting in a long-term increase in average temperatures worldwide (Keeley, Syphard, 2016). As temperatures continue to rise, environmental conditions become increasingly conducive to wildfires, leading to more frequent and severe events.

Moreover, climate change-driven alterations in weather patterns, including more intense precipitation events, can lead to increased biomass growth (Westerling, 2016). This dynamic, combining more intense precipitation with extended dry periods and higher temperatures, is likely to enhance fuel availability, creating conditions favorable to larger and more severe fires in many regions of the world (Donat et al., 2013; Pachauri et al., 2014).

Given its geographical location, Mexico stands as one of the countries most susceptible to the impacts of climate change (Murray-Tortarolo, 2021). This situation remarks the critical need for proactive measures to mitigate climate change effects and to enhance wildfire management strategies nationwide, with particular emphasis on Jalisco—a state notably vulnerable to these challenges.

4.2.3. *Land cover*

Land cover plays a crucial role in explaining the spatial variation of wildfire behavior, as it determines the distribution of fuels and interacts with prevailing weather conditions (Jardel-Peláez et al., 2012; Turner et al., 2015; Diaz-Avalos et al., 2016).

Our model effectively captured the impact of vegetation and land cover on wildfire size, aligning with the observed general patterns in our study. It demonstrated that different vegetation types exhibit distinct susceptibilities to fire, with certain types more likely to burn and contribute to wildfire occurrence.

The model fitted gave negative but significant coefficients for wetlands and tropical dry forests, indicating that wildfires tend to be smaller in these ecosystems compared to fires occurring in pine-oak forests. This asserts the pivotal role of pine-oak forests in shaping both the spatial distribution and magnitude of wildfires within the study area. Moreover, considering that tropical dry forests had the second-highest wildfire incidence among the vegetation covers in Jalisco, their significant association with wildfire size is not unusual. In contrast, wetlands typically experience minimal fire occurrence, meaning their spatial distribution strongly influences wildfire size by hindering fire spread.

4.2.4. NDVI

Numerous global studies have utilized NDVI to assess vegetation response and recovery post-wildfire events (e.g., Leon et al., 2012; Ba et al., 2022). Our findings, however, highlight NDVI's utility as a good indicator of both wildfire occurrence and size, suggesting its potential as a predictive tool for fire behavior.

Areas with low NDVI values are indicative of water-stressed vegetation, which can serve as easily ignitable fuel sources (Safyan et al., 2017). Our study revealed a strong relationship between low NDVI values and a higher frequency of wildfires. The latter could have implications for fire management practices and mitigation strategies. For instance, besides temperature and precipitation records, NDVI can serve as an early warning indicator of potential wildfire risk - lower NDVI values being indicative of increased flammability of vegetation - and managers and firefighters can prioritize resources and interventions. This could be particularly relevant during pronounced droughts and in ecosystems characterized by marked seasonal variations, such as oak and tropical dry forests (Jardel-Peláez et al., 2012)

In contrast, the association between higher NDVI values and larger wildfires in the model estimates suggests that regions with more abundant vegetation, leading to increased fuel availability, can experience more extensive wildfire episodes. This finding underscores the potential of implementing targeted fuel management practices in areas with high NDVI values. By continuously monitoring NDVI, authorities can identify areas with dense vegetation that are at potentially heightened risk, facilitating timely and strategic interventions. Employing methods such as controlled burns and mechanical thinning can effectively reduce fuel loads, thereby mitigating the likelihood of large-scale wildfires (Jardel-Peláez et al., 2014).

Utilizing NDVI as an indicator for targeted fuel management presents a cost-effective and efficient alternative to traditional methods commonly employed in Mexico, such as in situ observations by fire brigades (Balcázar, 2011). While the latter approach is valuable, it can be costly and time-consuming, often limited by the logistical challenges of covering extensive and potentially inaccessible areas. In contrast, satellite-based NDVI data offers an advantage due to its accessibility, comprehensive spatial coverage, and high temporal resolution (Chuvieco et al., 2004)

4.2.5. Proximity to roads and agricultural land

Mexico's National Forestry Commission reports that 31 % of wildfires in the country are intentional, with an additional 22 % originating from agricultural and farming activities (Conafor, 2023). In Jalisco, human activities have been identified as the source of up to 98 % of total wildfires (Semadet, 2021). This trend underscores the urgent need for comprehensive information on the causes of ignition and the integration of social factors into effective wildfire prevention strategies. However, in Mexico, and particularly in Jalisco, the determination of wildfire causes often remains inconclusive or is labeled as unknown. This issue largely arises from the challenge of identifying a cause when a fire is detected well after its ignition, a common scenario encountered by fire brigades (Michel-Fuentes, 2010). The prevalent ambiguity and lack of reliability in existing data highlight the critical necessity for enhancing databases and methodologies. Furthermore, it emphasizes the importance of adopting new technologies to refine the accuracy and comprehensiveness of wildfire cause identification.

In our study, we encountered the same challenge as the exact cause of individual fire events could not be discerned solely from satellite imagery. However, our analysis revealed a notable decrease in wildfire frequency with increasing distance from the nearest road and agricultural land. This pattern implies that roads and agricultural areas, often associated with human activities such as discarded cigarettes, intentional burns, or agricultural practices, act as potential sources of fire ignition. While our data does not explicitly differentiate between human-induced and natural wildfires, the higher concentration of ignition sources near roads and agricultural areas correlates with an increased number of wildfires, indicative of the significant role human activities play in wildfire occurrences at the regional scale. This aligns with previous studies, such as Castel-Clavera et al. (2022), who identified roads as having the strongest influence on fire occurrence among human-related factors, underscoring the role of accessibility in facilitating wildfires. They also emphasized the importance of interfaces between forests and agricultural lands as hotspots for fire activity, reinforcing our findings that human activities in these zones are key drivers of wildfires in Jalisco. This highlights the need for enhanced fire prevention strategies, particularly at the interface of human settlements and wildland areas.

Although Mexico has legal frameworks designed to regulate burns associated with agricultural activities, challenges arise when fires are intentionally set to convert forests into grasslands or croplands—a practice driven by the desire for land-use change (Balcázar, 2011). Addressing this issue necessitates tackling the underlying causes, which stem from intricate socioeconomic dynamics.

On the other hand, the prevalence of large wildfires in remote forested regions, as indicated by our model coefficients, emphasizes the challenges in responding to and controlling fires in areas where firefighting activities are more difficult. These findings underscore the importance of efficient detection systems, rapid response mechanisms, and adequate resources for managing wildfires in remote terrains. Crucially, this situation calls for the integration of technological advancements beyond traditional firefighting brigades, such as the implementation of early warning systems based on satellite imagery and remote sensing techniques.

Additionally, understanding the origins of these extensive wildfires is essential. For instance, in Jalisco's Natural Reserve Sierra de Manantlán, it has been reported that illegal agricultural activities are a significant contributor to the largest wildfires and areas burned (Balcázar, 2011). Illegal agriculture, often conducted in secluded forest regions to evade detection by authorities, results in fires that are harder to identify and manage due to their distance from human settlements. Addressing these underlying issues requires confronting the root causes of complex socioeconomic processes.

4.3. Spatial distribution of wildfires in Jalisco

4.3.1. Model validation and enhancement for wildfire prediction

Overall, a strong correlation was observed between real burned area values and those predicted by the model. Among the validation period years, 2018 exhibited the lowest percentage of error, followed by 2020, and then 2019. This pattern is attributed to the fact that, unlike 2018, which had a total burned area within the average, the burned surfaces in 2019 and 2020 were lower (2020) or higher (2019) than expected. Specifically, the notably larger error in 2019 was linked to the extensive scale of the fires that occurred that year.

Although the model was effective in estimating the burned area of small and medium-sized fires, its predictability was lower for larger events. Likewise, it was found that the maximum burned area estimates per episode did not exceed 3000 ha, indicating that the model did not predict the incidence of larger-scale wildfires.

To enhance the model's predictability, incorporating a term that considers the temporal dimension would be necessary. This means that the data should be defined by a process indexed in both time and space (Blangiardo and Cameletti, 2015). This interaction would allow for the inclusion of the effect of large-scale climatic variations. Moreover, given that the model was primarily calibrated with small and medium-sized fire data, its capacity to predict larger magnitude events was limited. Enhancing its accuracy could involve developing two distinct models:

one tailored for small-scale fires and another for larger fires. This targeted approach would better align predictions with the unique dynamics of each fire category. However, in this study, we found it critical to include all fire sizes to maintain the integrity of the spatial analysis at a regional scale. This approach ensures that our findings reflect the full extent of wildfire activity in Jalisco, as both small and large wildfires play a crucial role in shaping spatial patterns and fire dynamics across the landscape.

4.3.2. *Wildfire's spatial patterns and causal factors*

Based on model estimations, we identified four distinct fire-prone regions in the state of Jalisco, characterized by consistently higher concentrations of burned areas. The heightened fire activity within these regions is primarily attributed to the prevalence of pine-oak forests and tropical dry forests, vegetation covers observed to be more susceptible to burning throughout the study period.

The notable concentration of burned areas within these regions may also suggest an influence of anthropogenic activities on fire ignitions. While fires caused by lightning or other natural factors often exhibit a more random distribution (Krawchuk et al., 2009; Syphard et al., 2008), the observed clustering of fire-affected areas raises questions about the potential for human-induced wildfire incidents in these areas.

As previously stated, a vast majority of fires in Jalisco are attributed to human causes. Specifically, within the zones highlighted by our model, wildfires are commonly associated with intentional burning, agricultural clearing, and illegal activities (Semadet, 2021). These areas not only support significant agricultural activity—crucial for the local economy—but also harbor substantial forested lands. Furthermore, the central region, noted for its high population density, includes major urban centers like Guadalajara and Zapopan, amplifying the interface between human settlements and natural landscapes (Semadet, 2021).

The nominal range estimated by the model (approximately 3.74 km), indicates that wildfires occurring within this proximity tend to have similar sizes. This suggests that wildfires within this range can influence each other's behavior, potentially due to shared fuel sources; the spread of fire within a few kilometers affects the availability of fuel for subsequent events (Jardel-Peláez et al., 2014). This spatial correlation has practical applications, especially in planning prescribed burns or controlled fires. Fire managers can use this information to allocate resources strategically and implement prescribed burns more effectively. This approach is crucial for reducing fuel loads and minimizing the risk of larger, uncontrolled wildfires, particularly in ecosystems with a historical regime of frequent fire events, such as the forest ecosystems present in Jalisco (Jardel-Peláez et al., 2014).

While our modeling approach has opportunities for further enhancement, this study marks a significant milestone in wildfire research within the state of Jalisco. It provides a comprehensive regional overview of burned area distribution, offers insights into the overall pattern of wildfire risk across the state, and establishes a foundation for future research. Particularly, it highlights the identified fire-prone areas as prime candidates for localized studies and the implementation of tailored management strategies.

Additionally, within the context of Mexico, at the time this study was conducted, we are aware of only one other research project (Villar-Hernández et al., 2022) that has applied the INLA methodology to wildfire analysis in the country. Unlike our study, their approach did not incorporate the spatial component SPDE in the modeling process, underscoring the uniqueness and potential impact of our research in advancing the understanding of wildfire dynamics and management in Mexico.

4.3.3. *Study limitations and future directions*

We believe the chosen approach effectively met the objectives of this regional study, establishing a solid baseline for future research to build upon. As a regional-scale approach, this work lays the groundwork for more localized studies, particularly in the high-risk areas identified in our findings. However, we acknowledge certain limitations inherent in this approach, which may affect some aspects of the results.

One limitation of our study is the use of a single land cover layer from 2016. This choice ensured spatial consistency with our burned area data, as both shared high saptial resolution. Additionally, the dataset provided detailed, context-specific information on local vegetation, making it highly relevant for management and decision-making in Jalisco. However, incorporating multi-year land cover data would allow for the analysis of land cover changes over time, offering valuable insights into the relationship between land cover dynamics and wildfire activity—particularly regarding transitions from natural vegetation to anthropogenic landscapes. Future research could benefit from exploring this relationship, especially in localized studies where more detailed land cover data may be available. It's also essential that any land cover data remains specific to Jalisco and Mexico to ensure its relevance for local management and policy decisions.

In addition to land cover, another key variable that could enhance wildfire studies is the incorporation of fuel beds. Fuel beds provide a more accurate representation of the state of combustible material, offering insights into factors such as fuel availability, moisture content, type, arrangement, and quantity. These aspects play a fundamental role in influencing fire behavior and severity. While vegetation and land cover data offer valuable information, fuel beds reflect the actual conditions and risks driving fire events more precisely. In regional-scale studies like ours, quantifying fuel beds presents significant challenges due to data availability and scale. Nonetheless, for more localized studies, incorporating fuel beds would provide a deeper understanding of fire dynamics and allow for more targeted fire risk assessments. Integrating this data could enhance the precision of fire models and inform more effective management and mitigation strategies.

We also acknowledge that the meteorological variables used in our study, specifically precipitation and temperature, could be further refined in future research. Although remote sensing data provided comprehensive spatial coverage, enabling us to capture broad weather patterns affecting wildfire behavior across Jalisco, the datasets were resampled to match the resolution of our covariates and fire data, which did not improve their intrinsic accuracy. For more localized studies, incorporating meteorological station data would provide more precise weather information and enhance the understanding of wildfire behavior at finer scales. Additionally, using indices that integrate in situ observations with remote sensing data, such as drought indices, could simplify the interpretation and aggregation of weather variables. Future research could benefit from these approaches, particularly as more comprehensive datasets become available.

Regarding the model, a key limitation is the assumption of independence between the spatial and temporal dimensions. By treating these components separately, we may have overlooked potential spatio-temporal interactions. This simplification was necessary to reduce model complexity and computational demands, but it could limit the model's ability to fully capture dynamic processes. Addressing this limitation in future studies by integrating spatio-temporal models would provide a more comprehensive understanding of the relationship between space and time in wildfire behavior.

Despite these limitations, we are confident that our findings provide valuable insights into wildfire behavior and dynamics, laying a solid foundation for future research and informing management strategies in Jalisco. Addressing these limitations in subsequent studies will help refine the understanding of wildfire risk, ultimately contributing to more effective prevention and mitigation efforts in the region.

5. Conclusions

This study represents a significant advancement in understanding wildfire dynamics within Jalisco, highlighting the pivotal roles of climatic variability, land cover, and human activities in shaping wildfire patterns. Through our modeling approach, we've delineated fire-prone regions, identified key factors influencing wildfire behavior, and proposed improvements for future predictive modeling.

Our findings confirm that wildfires are more prevalent and expansive than agricultural burns, with specific vegetation types like pine-oak and tropical dry forests showing higher susceptibility to wildfires. These results are aligned with national trends and underscore the importance of integrated fire management strategies that consider both ecological and anthropogenic factors.

Temperature emerged as a critical factor, with our model reflecting how variations in this element correlate with changes in wildfire frequency and size. This relationship underscores the escalating impact of climate change on wildfire regimes, necessitating robust strategies to mitigate its effects and enhance resilience against future wildfire risks in the region.

Quantifying the effects of topography on wildfire behavior presented significant challenges, primarily due to the complex interactions between topographic features and various landscape elements, such as microclimate variations, fuel availability, and human activities. Conversely, NDVI emerged as a reliable indicator of wildfire behavior, emphasizing its potential as a predictive tool for assessing fire risk. This utility is enhanced by NDVI's accessibility, extensive spatial coverage, and high temporal resolution, making it valuable for fire management strategies.

The INLA-SPDE methodology has proven to be an innovative statistical tool, particularly within the context of wildfire research in Mexico, where its application remains relatively scarce. This analysis thus marks a significant contribution to wildfire modeling in the country. Additionally, the identification of specific fire-prone regions in Jalisco highlights the need for targeted fire management strategies that consider both ecological characteristics and human impacts in these areas.

Ultimately, this research not only sheds light on the current state of wildfire dynamics in Jalisco but also provides a solid foundation for future research. Furthermore, our findings confirm that Jalisco is among the Mexican states most affected by wildfires, highlighting the urgent need for policies focused on reducing wildfire risks and safeguarding both natural ecosystems and human communities.

Ethics

Not applicable.

CRediT authorship contribution statement

Somnath Chaudhuri: Visualization, Software, Formal analysis. **Camila Toledo-Jaime:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Pablo Juan:** Writing – review & editing, Supervision, Conceptualization. **Laura Serra:** Validation, Project administration. **Carlos Diaz-Avalos:** Writing – review & editing, Supervision, Conceptualization.

Declaration of Competing Interest

The manuscript is an original contribution that has not been published before, whole or in part, in any format, including electronically. All authors will disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations, that could inappropriately influence or be perceived to influence their work, within three years of beginning the submitted work.

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Authors' contributions

Camila Toledo-Jaime and Carlos Díaz-Avalos had the original idea for the paper. Carlos Díaz-Avalos and Pablo Juan designed and supervised the study. The bibliographic search was carried out by all the authors. Data collection and cleaning were performed by Somnath Chaudhuri and Camila Toledo-Jaime. The methods and statistical analysis were chosen and performed by Camila Toledo-Jaime, Somnath Chaudhuri, Laura Serra and Pablo Juan. Camila Toledo-Jaime conducted both the creation of tables and figures and the writing of the paper. The final editing was done by all authors. All authors reviewed and approved the manuscript.

Conflict of interest

The manuscript is an original contribution that has not been published before, whole or in part, in any format, including electronically. All authors will disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations, that could inappropriately influence or be perceived to influence their work, within three years of beginning the submitted work.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2024.122349.

Data Availability

Data will be made available on request.

References

Abatzoglou, J.T., Williams, A.P., Barbero, R., 2019. Global emergence of anthropogenic climate change in fire weather indices. Geophys. Res. Lett. 46 (1), 326–336.

Agresti, A., Caffo, B., 2002. Measures of relative model fit. Comput. Stat. data Anal. 39 (2), 127–136.

Alizadeh, M.R., Abatzoglou, J.T., Adamowski, J., Modaresi Rad, A., AghaKouchak, A., Pausata, F.S., Sadegh, M., 2023. Elevation-dependent intensification of fire danger in the western United States. Nat. Commun. 14 (1), 1773.

Amatulli, G., Perz-Cabello, F., De la Riva, J., 2007. Mapping lightning/human-caused forest fires occurrence under ignition point location uncertainty. Ecol. Model. 200 (3–4), 321–333.

Aragó, P., Juan, P., Díaz-Avalos, C., Salvador, P., 2016. Spatial point process modeling applied to the assessment of risk factors associated with forest wildfires incidence in Castellón, Spain. Eur. J. For. Res. 135, 451–464.

Ba, R., Song, W., Lovallo, M., Zhang, H., Telesca, L., 2022. Informational analysis of MODIS NDVI and EVI time series of sites affected and unaffected by wildfires. Phys. A: Stat. Mech. its Appl. 604, 127911.

Balcázar, 2011. *Patrones Geoecológicos de Incendios Forestales en la Reserva de la Biosfera Sierra de Manantlán.* [Tesis de Maestría, Universidad de Guadalajara], Jalisco, México.

Balch, J.K., Bradley, B.A., Abatzoglou, J.T., Nagy, R.C., Fusco, E.J., Mahood, A.L., 2017. Human-started wildfires expand the fire niche across the United States. Proc. Natl. Acad. Sci. 114 (11), 2946–2951.

Bárcenas-Pazos, G., González-Cabán, A., Rodríguez-Trejo, D.A., 2018. Evaluating the impact of fire suppression on forest structure and species composition in a Mexican pine-oak forest. Forests 9 (5), 268.

Blangiardo, M. & Cameletti, M. (2015). Spatial and spatio-temporal Bayesian models with R-INLA. John Wiley & Sons, Ltd.

Bountzouklis, C., Fox, D.M., Di Bernardino, E., 2021. Environmental Factors Affecting Wildfire Burned Area In South-Eastern France. 1970–2019. *Nat. Hazards Earth Syst. Sci. Discuss.* 2021, 1–24.

Bowman, D.M., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., Pyne, S.J., 2009. Fire in the Earth system. science 324 (5926), 481–484.

Castel-Clavera, J., Pimont, F., Opitz, T., Ruffault, J., Rivière, M., Dupuy, J.L., 2022. Disentangling the factors of spatio-temporal patterns of wildfire activity in south-eastern France. Int. J. Wildland fire 32 (1), 15–28.

Cerano-Paredes, J., Villanueva-Díaz, J., Cervantes-Martínez, R., Fulé, P., Yocom, L., Esquivel-Arriaga, G., Jardel-Peláez, E., 2015. Historia de incendios en un bosque de pino de la sierra de Manantlán, Jalisco, México. Bosque (Valdivia) 36 (1), 41–52.

Challenger, A., & Soberón, J. (2008). Los ecosistemas terrestres, en Capital natural de México, Vol. I: Conocimiento actual de la biodiversidad. Comisión Nacional para el Conocimiento y Uso de la Biodiversidad CONABIO, México.

Chaudhuri, S., Saez, M., Varga, D., Juan, P., 2023a. Spatiotemporal modeling of traffic risk mapping: A study of urban road networks in Barcelona, Spain. Spat. Stat. 53, 100722.
Chaudhuri, S., Juan, P., Saurina, L.S., Varga, D., Saez, M., 2023b. Modeling spatial dependencies of natural hazards in coastal regions: a nonstationary approach with barriers. Stochastic Environmental Research and Risk Assessment 37 (11), 4479–4498.
Chuvieco, E., Cocero, D., Riano, D., Martin, P., Martınez-Vega, J., De La Riva, J., Pérez, F., 2004. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. Remote Sens. Environ. 92 (3), 322–331.
Chuvieco, E., Lizundia-Loiola, J., Pettinari, M.L., Ramo, R., Padilla, M., Tansey, K., Plummer, S., 2018.). Generation and analysis of a new global burned area product based on MODIS 250 m reflectance bands and thermal anomalies. Earth Syst. Sci. Data 10 (4), 2015–2031.
CONAFOR) (2022). Programa Nacional de Prevención Contra Incendios Forestales: resultados 2021. Retrieved from website: ⟨https://www.gob.mx/cms/uploads/attachment/⟩ file/ 604834/Cierre_ de_la_Temporada_2021.PDF.
CONAFOR) (2023). Coordinación General de Restauración y Conservación: Gerencia de Manejo de Fuego 2023. Retrieved from website: ⟨https://www.gob.mx/cms/uploads/attachment/file/879026/Cierre_de_la_Temporada_2023.pdf⟩.
CONAFOR & SEMADET. (2020). Mapa de Cobertura del Suelo del Estado de Jalisco al año base 2016 [Vector]. Escala 1:75,000. Versión 1.3. México: Comisión Nacional Forestal y Secretaría de Medio Ambiente y Desarrollo Territorial del Gobierno del Estado de Jalisco.
CONAGUA. (2023). Índice Estandarizado de Precipitación. Retrieved from webpage: ⟨https://smn.conagua.gob.mx/es/climatologia/monitor-de-sequia/spi⟩.
R. Core Team. (2021). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. Vienna, Austria. ⟨https://www.R-project.org/⟩.
Corona-Núñez, R.O., Campo, J.E., 2023. Climate and socioeconomic drivers of biomass burning and carbon emissions from fires in tropical dry forests: A Pantropical analysis. Glob. Change Biol. 29 (4), 1062–1079.
Corona-Núñez, R.O., Li, F., Campo, J.E., 2020. Fires represent an important source of carbon emissions in Mexico. Glob. Biogeochem. Cycles 34 (12) e2020GB006815.
Cuevas-Arias, C.T., Vargas, O., Rodríguez, A., 2008. Solanaceae diversity in the state of Jalisco, Mexico. Rev. Mex. De. Biodivers. 79 (1), 67–79.
Díaz-Avalos, C., Peterson, D.L., Alvarado, E., Ferguson, S.A., Besag, J.E., 2001. Space-time modelling of lightning-caused ignitions in the Blue Mountains, Oregon. Can. J. For. Res. 31 (9), 1579–1593.
Díaz-Avalos, C., Juan, P., Serra-Saurina, L., 2016. Modeling fire size of wildfires in Castellon (Spain), using spatiotemporal marked point processes. For. Ecol. Manag. 381, 360–369.
Didan, K., 2015. MOD13Q1 MODIS/Terra vegetation indices 16-day L3 global 250m SIN grid V006. NASA eosdis Land Process. daac 10 (730), 415.
Donat, M.G., Alexander, L.V., Yang, H., Durre, I., Vose, R., Dunn, R.J., Kitching, S., 2013. Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The HadEX2 dataset. J. Geophys. Res.: Atmospheres 118 (5), 2098–2118.
Falk, D.A., Heyerdahl, E.K., Brown, P.M., Farris, C., Fulé, P.Z., McKenzie, D., Van Horne, M.L., 2011. Multi-scale controls of historical forest-fire regimes: new insights from fire-scar networks. Front. Ecol. Environ. 9 (8), 446–454.
Flannigan, M.D., Wotton, B.M., Ziga, S., 1998. A study on the interpolation of fire danger using radar precipitation estimates. Int. J. Wildland Fire 8 (4), 217–225.
Fule, P.Z., Covington, W.W., 1996. Changing fire regimes in Mexican pine forests: ecological and management implications. J. For. 94 (10), 33–38.
Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. data 2 (1), 1–21.
Gallardo-García, V., López-Sánchez, C.A., González-Espinosa, M., Meave, J.A., 2016. Effects of altered fire regimes on forest structure and composition in lowland pine-oak forests in Mexico. Plant Ecol. 217 (2), 197–209.
Gill, L., Taylor, A.H., 2009. Top-down and bottom-up controls on fire regimes along an elevational gradient on the east slope of the Sierra Nevada, California, USA. Fire Ecol. 5, 57–75.
Gutierrez, A.A., Hantson, S., Langenbrunner, B., Chen, B., Jin, Y., Goulden, M.L., Randerson, J.T., 2021. Wildfire response to changing daily temperature extremes in California's Sierra Nevada. Sci. Adv. 7 (47), eabe6417.
Hartung, M., Carreño-Rocabado, G., Peña-Claros, M., van der Sande, M.T., 2021. Tropical dry forest resilience to fire depends on fire frequency and climate. Front. For. Glob. Change 4, 755104.
Hawbaker, T.J., Radeloff, V.C., Syphard, A.D., Zhu, Z., Stewart, S.I., 2008. Detection rates of the MODIS active fire product in the United States. Remote Sens. Environ. 112 (5), 2656–2664.
Hering, A.S., Bell, C.L., Genton, M.G., 2009. Modeling spatio-temporal wildfire ignition point patterns. Environ. Ecol. Stat. 16, 225–250.
Heyerdahl, E.K., Alvarado, E., 2003. Influence of climate and land use on historical surface fires in pine-oak forests, Sierra Madre Occidental, Mexico. Fire and climatic change in temperate ecosystems of the western Americas. New York, NY: Springer, New York, pp. 196–217.
Heyerdahl, E.K., Brubaker, L.B., Agee, J.K., 2001. Spatial controls of historical fire regimes: a multiscale example from the interior west, USA. Ecology 82 (3), 660–678.
Holden, Z.A., Morgan, P., Evans, J.S., 2009. A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area. For. Ecol. Manag. 258 (11), 2399–2406.
Holden, Z.A., Swanson, A., Luce, C.H., Jolly, W.M., Maneta, M., Oyler, J.W., Affleck, D., 2018. Decreasing fire season precipitation increased recent western US forest wildfire activity. Proc. Natl. Acad. Sci. 115 (36), E8349–E8835.
Ibarra-Montoya, J.L., Huerta-Martínez, F.M., 2016. Modelado espacial de incendios: una herramienta predictiva para el Bosque La Primavera. Jalisco México. *Rev. Ambient. Água* 11, 35–49.
INEGI. (2011). *Conjunto de Carreteras y Vialidades* [Vector]. Escala 1:50,000. México: Instituto Nacional de Estadística y Geografía.
INEGI. (2012). Continuo de Elevaciones Mexicano [TIFF]. Resolución 12 m. México: Instituto Nacional de Estadística y Geografía.
INEGI. (2013). Conociendo Jalisco. Retrieved from website: ⟨https://www.inegi.org.mx/contenido/productos/⟩ prod_serv/contenidos/espanol/bvinegi/productos/estudios/conociendo/JALISCO.pdf.
Jardel, E.J., Ramírez, V.R., Castillo, N.F., García, R.S., Balcázar-Medina, O.E., Chacón-Mathieu, J.C., Morfín, J.E., 2006. Manejo del fuego y restauración de bosques en la Reserva de la Biosfera Sierra de Manantlán. México. *Incendios For. México Y. Madr. Mundi-Prensa-CONAFOR* 216–242.
Jardel-Peláez, E.J., Morfín-Ríos, J.E., Alvarado, E., Pérez-Salicrup, D., 2012. Caracterización de los regímenes de incendios en ecosistemas forestales del Occidente de México. Universidad de Guadalajara. Cons. Estatal De. Cienc. Y. Tecnol. ía De. Jalisco 42 ([Technical Report]).
Jardel-Peláez, E.J., Pérez-Salicrup, D., Alvarado, E., Morfín-Ríos, J.E., 2014. Principios y criterios para el manejo del fuego en ecosistemas forestales: guía de campo. Com. óN. Nac. For. (CONAFOR), Guadalaj., Jalisco, México.
Jolly, W.M., Cochrane, M.A., Freeborn, P.H., Holden, Z.A., Brown, T.J., Williamson, G.J., Bowman, D.M., 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. Nat. Commun. 6 (1), 7537.
Keeley, J.E., Syphard, A.D., 2016. Climate change and future fire regimes: examples from California. Geosciences 6 (3), 37.
Keeley, J.E., Zedler, P.H., 1998. Ecology and evolution of pine life histories. Ann. For. Sci. 69 (4), 445–453.
Krawchuk, M.A., Cumming, S.G., Flannigan, M.D., 2009. Predicted changes in fire weather suggest increases in lightning fire initiation and future area burned in the mixedwood boreal forest. Clim. Change 92 (1-2), 83–97.
Leon, J.R.R., Van Leeuwen, W.J., Casady, G.M., 2012. Using MODIS-NDVI for the modeling of post-wildfire vegetation response as a function of environmental conditions and pre-fire restoration treatments. Remote Sens. 4 (3), 598–621.
Lindgren, F., Rue, H., Lindström, J., 2011. An explicit link between Gaussian fields and Gaussian Markov random fields: The stochastic partial differential equation approach. J. R. Stat. Soc.: Ser. B (Stat. Methodol.) 73 (4), 423–498.
Littell, J.S., McKenzie, D., Peterson, D.L., Westerling, A.L., 2009. Climate and wildfire area burned in western US eco-provinces, 1916–2003. Ecol. Appl. 19 (4), 1003–1021.
Mansoor, S., Farooq, I., Kachroo, M.M., Mahmoud, A.E.D., Fawzy, M., Popescu, S.M., Ahmad, P., 2022. Elevation in wildfire frequencies with respect to the climate change. J. Environ. Manag. 301, 113769.
Martino, S., Riebler, A., 2019. Integrated nested Laplace approximations (INLA). arXiv Prepr. arXiv 1907, *01248*.
Martins, T.G., Simpson, D., Lindgren, F., Rue, H., 2013. Bayesian computing with INLA: new features. Comput. Stat. Data Anal. 67, 68–83.
Matérn, B. (1960). Spatial variation. Stochastic models and their application to some problems in forest surveys and other sampling investigations.
McKenzie, D., Gedalof, Z., Peterson, D.L., Mote, P., 2004. Climatic change, wildfire, and conservation. Conserv. Biol. 18 (4), 890–902.
McKenzie, D., Hessl, A.E., Kellogg, L.K.B., 2006. Using neutral models to identify constraints on low-severity fire regimes. Landsc. Ecol. 21, 139–152.
McKenzie, D., Miller, C., Falk, D.A., 2011. The landscape ecology of fire, 213. Springer Science & Business Media.
Méndez-Toribio, M., Meave, J.A., Zermeño-Hernández, I., Ibarra-Manríquez, G., 2016. Effects of slope aspect and topographic position on environmental variables, disturbance regime and tree community attributes in a seasonal tropical dry forest. J. Veg. Sci. 27 (6), 1094–1103.
Michel-Fuentes., J.M. (2010). *Caracterización y clasificación de combustibles forestales para el manejo del fuego en áreas protegidas de México*. [Tesis de Maestría, Universidad de Guadalajara]. Jalisco, México.
Montoya, L.E., Corona-Núñez, R.O., Campo, J.E., 2023. Fires and their key drivers in Mexico. Int. J. Wildland Fire 32 (5), 651–664.
Moraga, P., Dean, C., Inoue, J., Morawiecki, P., Noureen, S.R., Wang, F., 2021. Bayesian spatial modelling of geostatistical data using INLA and SPDE methods: A case study predicting malaria risk in Mozambique. Spat. Spatio-Tempo Epidemiol. 39, 100440.
Moreno-Ruiz, J.L., Siebe, C., González-Elizondo, M.S., 2013. Effects of fire suppression on plant community structure and regeneration in a Mexican pine-oak forest. Int. J. Wildland Fire 22 (3), 374–383.
Murray-Tortarolo, G.N., 2021. Seven decades of climate change across Mexico. Atm. ósfera 34 (2), 217–226.
Neger, C., León-Cruz, J.F., Galicia Sarmiento, L., Manzo-Delgado, L.D.L., 2022. Spatiotemporal dynamics, causes and effects of mega-wildfires in Mexico. Madera Y. Bosques 28 (2).
Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., … & van Ypserle, J.P. (2014). Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change (p. 151). Ipcc.
Parks, S.A., Parisien, M.A., Miller, C., 2012. Spatial bottom-up controls on fire likelihood vary across western North America. Ecosphere 3 (1), 1–20.

Pennington, R.T., Lavin, M., Oliveira-Filho, A., 2009. Woody plant diversity, evolution, and ecology in the tropics: perspectives from seasonally dry tropical forests. Annu. Rev. Ecol., Evol., Syst. 40, 437–457.

Pettinari M.L., Otón, G. (2020). ESA Climate Change Initiative–Fire_cci D4. 2.2 Product User Guide-AVHRR-Long Term Data Record (PUG-LTDR). Technical Report.

Pimont, F., Fargeon, H., Opitz, T., Ruffault, J., Barbero, R., Martin StPaul, N., Dupuy, J. L., 2020. Prediction of regional wildfire activity with a probabilistic Bayesian framework. bioRxiv, 2020-05.

Pyne, S.J., Andrews, P.L., Laven, R.D., 1996. Introduction to Wildland Fire. John Wiley and Sons, New York.

Ramírez, G., de Rivera, M.M.S.D., Morales, C.J.P., Ramírez, M.B., Ángulo, G.J.L., Tinajero, R.P., Gallo, L.N.G., 2013. Gobierno del Estado de Jalisco. Reg. De. Jalisco. Retrieved webpage. ⟨http://www.jalisco.gob.mx/es/jalisco/regiones⟩.

Reid, C.E., Brauer, M., Johnston, F.H., Jerrett, M., Balmes, J.R., Elliott, C.T., 2016. Critical review of health impacts of wildfire smoke exposure. Environ. Health Perspect. 124 (9), 1334–1343.

R-INLA Project. (2020). ⟨https://www.r-inla.org⟩.

Rodríguez-Trejo, D.A., 2008. Fire regimes, fire ecology, and fire management in Mexico. AMBIO: a J. Hum. Environ. 37 (7), 548–556.

Rodríguez-Trejo, D.A., Fulé, P.Z., 2003. Fire ecology of Mexican pines and a fire management proposal. Int. J. Wildland Fire 12 (1), 23–37.

Rothermel, R.C. (1983). How to predict the spread and intensity of forest and range fires (Vol. 143). US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.

Rue, H., Martino, S., Chopin, N., 2009. Approximate Bayesian inference for latent Gaussian models by using integrated nested laplace approximations. J. R. Stat. Soc.: Ser. B (Stat. Methodol.) 71 (2), 319–392.

Rue, H., Riebler, A., Sørbye, S.H., Illian, J.B., Simpson, D.P., Lindgren, F.K., 2017. Bayesian computing with INLA: A review. Annu. Rev. Stat. Its Appl. 4 (1), 395–421.

Safyan, O., Murat, Y., Musa, A., et al., 2017. Evaluation of drought effects on vegetation cover using remote sensing. Open Geosci. 9 (1), 424–437.

SEMADET). (2021). Programa para Manejo del Fuego en el Estado de Jalisco. Gobierno del Estado de Jalisco. Retrieved from webpage: ⟨https://semadet⟩ .jalisco.gob.mx/sites/semadet.jalisco.gob.mx/files/manejodelfuego.pdf.

Serra, L., Saez, M., Juan, P., Varga, D., Mateu, J., 2014b. A spatio-temporal Poisson hurdle point process to model forest fires. Stoch. Environ. Res. Risk Assess. 28 (7), 1671–1684.

Serra, L., Saez, M., Mateu, J., Varga, D., Juan, P., Díaz-Ávalos, C., Rue, H., 2014a. Spatio-temporal log-Gaussian Cox processes for modelling wildfire occurrence: the case of Catalonia, 1994–2008. Environ. Ecol. Stat. 21, 531–563.

Starkweather, J., 2018. Reference category and interpreting regression coefficients in r. Res. Matters, Benchmarks Online Retrieved Dec. 19, 2020.

Stavi, I., 2019. Wildfires in grasslands and shrublands: A review of impacts on vegetation, soil, hydrology, and geomorphology. Water 11 (5), 1042.

Sutomo, van Etten, E.J., 2023. Fire impacts and dynamics of seasonally dry tropical forest of East Java, Indonesia. Forests 14 (1), 106.

Syphard, A.D., Radeloff, V.C., Keuler, N.S., Taylor, R.S., Hawbaker, T.J., Stewart, S.I., Clayton, M.K., 2008. Predicting spatial patterns of fire on a southern California landscape. Int. J. Wildland Fire 17 (5), 602–613.

Turner, M.G., Gardner, R.H., Turner, M.G., Gardner, R.H., 2015. Introduction to landscape ecology and scale. Landsc. Ecol. Theory Pract.: Pattern Process 1–32.

Vehtari, A., Gelman, A., Gabry, J., 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. 27, 1413–1432.

Villar-Hernández, B.D.J., Pérez-Elizalde, S., Rodríguez-Trejo, D.A., Pérez-Rodríguez, P., 2022. Análisis espacio temporal de la ocurrencia de incendios forestales en el estado mexicano de Oaxaca. Rev. Mex. De. Cienc. For. 13 (74), 120–144.

Villers-Ruiz, L., Chuvieco, E., Aguado, I., 2012. Application of the canadian fire weather index in a National Park of Central Mexico. Rev. Mex. De. Cienc. For. 3 (11), 25–40.

Westerling, A.L., 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philos. Trans. R. Soc. B: Biol. Sci. 371 (1696), 20150178.

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. science 313 (5789), 940–943.

Wiedinmyer, C., Neff, J.C., 2007. Estimates of CO2 from fires in the United States: implications for carbon management. Carbon Balance Manag. 2 (1), 1–12.

Xi, Z., 2019. Model-based reliability analysis with both model uncertainty and parameter uncertainty. J. Mech. Des. 141 (5), 051404.

Yang, J., Tian, H., Tao, B., Ren, W., Kush, J., Liu, Y., Wang, Y., 2014. Spatial and temporal patterns of global burned area in response to anthropogenic and environmental factors: reconstructing global fire history for the 20th and early 21st centuries. J. Geophys. Res.: Biogeosciences 119 (3), 249–263.

Yin, Y., Bloom, A.A., Worden, J., Saatchi, S., Yang, Y., Williams, M., Schimel, D., 2020. Fire decline in dry tropical ecosystems enhances decadal land carbon sink. Nat. Commun. 11 (1), 1900.

Zhang, Y., Biswas, A., 2017. The effects of forest fire on soil organic matter and nutrients in boreal forests of North America: a review. Adapt. Soil Manag.: Theory Pract. 465–476.

Zhao, H., Zhang, Z., Ying, H., Chen, J., Zhen, S., Wang, X., Shan, Y., 2021. The spatial patterns of climate-fire relationships on the Mongolian Plateau. Agric. For. Meteorol. 308, 108549.