Different Factors for Different Causes: Analysis of the Spatial Aggregations of Fire Ignitions in Catalonia (Spain)

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The present study analyzes the effects of different socioeconomic factors on the frequency of fire ignition occurrence, according to different original causes. The data include a set of documented ignition points in the region of Catalonia for the period 1995–2008. The analysis focused on the spatial aggregation patterns of the ignitions for each specific ignition cause. The point-based data on ignitions were interpolated into municipality-level information using kernel methods as the basis for defining five ignition density levels. Afterwards, the combination of socioeconomic factors influencing the ignition density levels of the municipalities was analyzed for each documented cause of ignition using a principal component analysis. The obtained results confirmed the idea that both the spatial aggregation patterns of fire ignitions and the factors defining their occurrence were specific for each of the causes of ignition. Intentional fires and those of unknown origin were found to have similar spatial aggregation patterns, and the presence of high ignition density areas was related to high population and high unemployment rates. Additionally, it was found that fires originated from forest work, agricultural activities, pasture burning, and lightning had a very specific behavior on their own, differing from the similarities found on the spatial aggregation of ignitions originated from smokers, electric lines, machinery, campfires, and those of intentional or unknown origin.

KEY WORDS: Ignition causes; socioeconomic factors; spatial aggregation

1. INTRODUCTION

Fire ignitions display specific spatial and temporal aggregation patterns depending on the causes that originate them.1,2,4 In general, it can be said that these patterns match the spatial distributions of the environmental and socioeconomic factors inducing their ignition occurrence. In this sense, identifying the possible factors driving their patterns of aggregation and assessing the risk of fire ignition occurrence are key issues for the adequate design and implementation of fire prevention measures.5–7 However, there are methodological and data limitations that preclude, in many cases, the explicit analysis of specific causes. For example, previous studies addressing socioeconomic or environmental factors related to the occurrence of human-associated ignitions often aggregate all the potential human-associated causes in a single category, or simplify the analysis by grouping them into a few categories such as intentional, accidental, restarted, negligence related, or of unknown origin.2,3,8–10 Some of these categories (e.g., intentional or restarted fires) can be regarded as close to their ultimate cause, and their origin and influencing
factors can be assumed to be fairly common within a regional frame. However, fires classified as accidental or due to negligence often include various specific and very different causes: e.g., negligence fires can be derived from burnings of bushes, pastures, agricultural waste, or human waste, but also from campfires, smokers, or forest works, whereas accidental fires may be originated from railroads, electric lines, military exercises, engines and machinery, among others.

The analysis of human originated fires by categories or groups of causes should be considered a vast improvement for understanding the factors behind their occurrence, compared to the alternative of using a single category for human-associated ignitions. However, it can result in combining events that often have different spatial and temporal occurrence patterns, as has been found in previous studies.\(^{(2-4,11-15)}\)

In this context, we assume that including additional categories in the potential causes related to an ignition, and analyzing their specific aggregation patterns, would improve the recognition of their specific occurrence patterns, and would also enhance the chances to accurately identify the related factors underlying the recurrence of fire ignitions.\(^{(6)}\) Thus, the knowledge obtained can provide a better framework for designing cause-specific fire prevention measures to reduce the number of ignitions and protect valuable resources.\(^{(4,14,16)}\)

Nevertheless, this analysis can be performed at different spatial scales. For example, regular grids can be used to display the occurrence or frequency of fire ignitions at this scale, and then compared with potential influencing factors.\(^{(5,17-21)}\) Other studies have analyzed the effect of aggregated factors on the number of ignitions occurring inside administrative limits, such as municipalities or counties.\(^{(22-25)}\) In this case, the study of the aggregation pattern of fire ignitions allows the characterization of events related to proxies or predictors based on socioeconomic indicators from historical census. This type of analysis implies loss of information about fine-scale variations in the spatial occurrence of ignitions, and potential errors due to spatial inaccuracies in recording the ignition points.\(^{(26)}\) However, it substantially enhances the modeling potential of the analysis.

To bridge these two approaches, kernel-based methods have recently been used to convert point-based data into continuous information about fire occurrence densities.\(^{(1,4,7,26)}\) These methods can generate ignition density information for a given administrative scale, which can then be used for further analyses of influencing factors.

In the present study we set out to analyze the effects of different socioeconomic factors on the frequency of fire ignition occurrence. For this purpose, the spatial aggregation patterns of fire ignitions in the region of Catalonia were analyzed independently for each specific ignition cause. The spatial analysis of the segregated ignitions was then used as a basis to interpolate the point-based data on ignitions into municipality-level information, highlighting differences in both the aggregating pattern of ignitions and the factors determining them.

2. MATERIAL AND METHODS

2.1. Catalonia and its Recent Fire Ignition History

The area of study encloses the whole region of Catalonia, in the northeast of Spain, covering 32,000 km\(^2\). The region is recurrently affected by forest fires, with some severe years: in 1994, 1,217 fires affected more than 76,500 ha, which prompted the government to make additional efforts to record the locations of the fire ignitions and to investigate their causality. During the studied period, covering the time frame 1995–2008, a total of 9,534 fires larger than 100 m\(^2\) were recorded (Table I).

Catalonia is one of the most populated regions of Spain, with over 7 million inhabitants. The demographic distribution is not homogeneous. It is clustered in some areas, usually near the coast (e.g., the city of Barcelona), and leaves large underpopulated areas. The region is divided into 946 municipalities (Fig. 1), also highly heterogeneous in size and socioeconomic characteristics. This socioeconomic variability is expected to influence the aggregation patterns of the ignitions.

| Cause                       | Number | Percentage |
|-----------------------------|--------|------------|
| Intentional (int)           | 2,354  | 24.69      |
| Agriculture (agr)           | 1,398  | 14.66      |
| Unknown (unk)               | 1,087  | 11.40      |
| Lightning (lig)             | 1,025  | 10.75      |
| Smokers (smo)               | 314    | 3.29       |
| Electric lines (ele)        | 356    | 3.73       |
| Forest work (for)           | 262    | 2.75       |
| Machinery (mac)             | 188    | 1.98       |
| Campfires (cam)             | 1,398  | 14.66      |
| Pasture burning (pas)       | 1,451  | 15.22      |
| Others                      | 1,087  | 11.40      |

Table I: Number of Ignitions Recorded by Cause in Catalonia for the Period 1995–2008
2.2. Ignition Density Estimation Using Kernel Methods

Kernel methods were applied to estimate variation in the density of fire ignitions. The kernel method is a nonparametric technique that uses the allocation of the fire ignitions as input to generate a continuous estimation of the accumulated density, based on probability density functions.\(^{(27,28)}\) Mathematically, the kernel density function for \(n\) observations can be defined as:

\[
\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K(u_i),
\]

for \(u_i = (x - X_i) / h\), where \(K\) is the kernel function, \(h\) is the bandwidth or smoothing factor, and \(x\) is the value of the observed variables. In the case of point events like ignitions, \(X_i\) corresponds to the vector of coordinates of the ignition, and therefore the difference \((x - X_i)\) refers to the distance between a point where the density function is to be estimated and each of the observed events used to define the density. In the present study, we used the spatial statistic package SPlancs\(^{(29)}\) adapted for R\(^{(30)}\) to estimate the probability densities. A quartic kernel function with a fixed bandwidth was applied as a method for correcting the border effect.\(^{(31,32)}\)

A characteristic of kernel methods is their flexibility, and the final result depends more on selecting an adequate magnitude for the radius of search or bandwidth \(h\), than on the selection of the kernel function (normal, triangular, Gaussian, or quartic), or on the method for selecting the radius of search (fixed or adaptive).\(^{(33,34)}\) Therefore, the selection of the bandwidth took into account both the size of the municipalities and the spatial distribution of the ignitions, following the objectives of the study. First, we compared the theoretical radius of the mean sized municipality (4119.4 m) with the mean random distance (RD\(_{\text{mean}}\)) between ignitions per municipality, multiplied by 2 (following).\(^{(26,35)}\)

A preparatory analysis of the spatial distribution of the fire ignitions was also implemented in order to identify spatially aggregated ignition causes.
The spatial aggregation analysis calculated the observed mean distance between ignitions (OMD), the expected mean distance for the total area of study (EMD), the nearest neighbor ratio (NNR = OMD/EMD), and the Z score, indicating how much NNR deviated from a fully random distribution of the ignitions (Table II).

The preparatory analysis indicated that all the ignitions, per cause, were spatially aggregated. The \( R_{\text{mean}} \) value was found to vary substantially according to the ignition cause, and so was used to define the bandwidth for the kernel density function for each set of ignitions. Hence, to study the intentional \( (\text{int}) \) ignitions, a bandwidth of 4,000 m was applied, 5,000 m for those whose origin was agriculture \( (\text{agr}) \), 6,000 m for those whose cause was lightning or unknown \( (\text{lig, unk}) \), 7,000 m for ignitions caused by smokers \( (\text{smo}) \), and 8,000 m for ignitions caused by campfires, pasture burning, forest work, or electric lines \( (\text{cam, pas, for, ele}) \).

### 2.3. Converting Fire Densities into Municipal-Level Risk Indices

Modeling the effect of socioeconomic factors on the risk of occurrence of fire ignitions at the municipal level requires harmonizing and scaling the data.\(^{35}\) This harmonizing process includes converting the ignition probability densities into a single value for each of the municipalities. For this purpose, we generated a square grid of points \( 500 \times 500 \) m, where the probability densities of the ignitions were estimated for each of the ignition causes separately, for the period 1995–2008. The average value of the points within each municipality was then calculated. Finally, one of five ignition density classes was assigned to each municipality (range levels: very low, low, medium, high, and very high).

We selected a number of potential predictors of ignition density variation among municipalities (Table III): area of the municipality \( (\text{Area}, \text{km}^2) \), mean elevation of the municipality, in meters above sea level \( (\text{Ele}, \text{m a.s.l.}) \), population density in 2001 \( (\text{Pop2001}, \text{inhabitants per km}^2) \), change in population between 1998 and 2008 \( (\text{PopVar98_08}, \text{percentage}) \), unemployment \( (\text{Unemploy}, \text{percentage versus total population}) \), unemployment of active population \( (\text{Unemploy16_65}, \text{percentage versus population ages 16 to 65}) \), vehicle density in 2002 \( (\text{VehicDens}, \text{vehicles registered per 1,000 inhabitants}) \), house density in 2001 \( (\text{HouseDens}, \text{houses per km}^2) \), households capacity in 2001 \( (\text{Household}, \text{houses per inhabitant}) \), delinquency in 2001 \( (\text{Conflict, registered felonies per house}) \), rural relevance in 1999 \( (\text{PRural, percentage of rural land}) \), agricultural relevance in 1999 \( (\text{PAgr, percentage of labored land}) \), forestry relevance in 2001 \( (\text{PFor, percentage of forest land}) \), pasture utilization in 2000 \( (\text{PPast, percentage of pasture land}) \), cattle presence \( (\text{CattleDens}, \text{bovine and equine cattle head per km}^2) \), agricultural mechanization in 1999 \( (\text{AgrMachines}, \text{number of tractors, harvesters, etc. per km}^2) \), camping presence in 2002 \( (\text{CampDens}, \text{number of campsites per km}^2) \), and hotel presence in 2002 \( (\text{HotelDens}, \text{number of hotels per km}^2) \).

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### Table II. Spatial Aggregation Analysis of the Ignitions, According to Their Cause

| Cause                  | 2 × RD\text{mean} | EMD  | OMD  | NNR  | ZS  |
|------------------------|-------------------|------|------|------|-----|
| Intentional (int)      | 3.693.1           | 2,441.6 | 892.9 | 0.37 | −58.87 |
| Agriculture (agr)      | 4.756.6           | 3,158.5 | 1,762.6 | 0.55 | −31.61 |
| Unknown (unk)          | 5.584.6           | 3,602.3 | 1,891.1 | 0.52 | −29.96 |
| Lightning (lig)        | 5.584.6           | 3,653.7 | 2,231.9 | 0.61 | −23.83 |
| Smokers (smo)          | 7.345.5           | 4,683.5 | 2,631.6 | 0.56 | −20.44 |
| Electric lines (ele)   | 7.973.4           | 5,034.8 | 3,035.2 | 0.60 | −17.07 |
| Forest work (for)      | 9.496.6           | 3,329.2 | 3,751.9 | 1.13 | 4.58  |
| Machinery (mac)        | 10.111.8          | 5,987.7 | 4,064.9 | 0.68 | −10.89 |
| Campfires (cam)        | 11.069.8          | 6,921.3 | 4,054.4 | 0.59 | −12.83 |
| Pasture burning (pas) | 13.068.1          | 7,588.5 | 3,509.9 | 0.46 | −14.10 |

OMD: mean observed distance between ignitions, EMD: expected mean distance for the total area of study, NNR: nearest neighbor ratio, ZS: Z score.

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### Table III. Socioeconomic Variables Included in the Analysis

| Variable                  | Mean    | Standard Deviation |
|---------------------------|---------|--------------------|
| Area                      | 30.8    | 34.9               |
| Ele                       | 461.7   | 413.6              |
| Pop2001                   | 373.0   | 1,455.5            |
| PopVar98_08               | 17.5    | 19.1               |
| Unemploy                  | 0.02    | 0.01               |
| Unemploy16_65             | 0.03    | 0.02               |
| VehicDens                 | 937.4   | 2,665.1            |
| HouseDens                 | 106.5   | 418.5              |
| Household                 | 0.28    | 0.02               |
| Conflict                  | 0.08    | 0.09               |
| PRural                    | 0.64    | 0.27               |
| P Agr                     | 0.30    | 0.26               |
| P For                     | 0.20    | 0.20               |
| P Past                    | 0.06    | 0.14               |
| CattleDens                | 16.1    | 26.6               |
| AgrMachines               | 4.1     | 3.9                |
| CampDens                  | 0.02    | 0.07               |
| HotelDens                 | 0.12    | 0.47               |
Some of the variables were retrieved from databases of national and regional institutes such as the Spanish National Institute for Statistics (INE) and the Statistics Institute of Catalonia (Idescat). The variables concerning population and agriculture were based on the Censo de Población y Viviendas de 2001, the Censo Agrario de 1999, and the Censo Agrario de 2009. These censuses provided information about the state and change of different socioeconomic variables at the municipal level during the study period.

The portfolio of socioeconomic variables was first analyzed using correlation matrices and principal component analysis (PCA), in order to identify noteworthy correlations and confounding effects between the variables considered. In some cases, the variables were transformed using the natural logarithms in order to reduce the effects of outliers, and to reduce strong deviations from normality. More complex transformations were avoided in order to retain the original variables as much as possible. Finally, the main axes resulting from the PCA, and the highest ignition levels, were combined to form the results.

3. RESULTS

3.1. Spatial Aggregation Patterns

The spatial distribution of ignition densities at the municipal level showed clearly different patterns, depending on the cause of the ignition (Figs. 2 and 3). For example, densities of ignitions caused intentionally (int), those whose cause was not identified (unk), or those originating from campfires (cam) followed similar spatial patterns. In this case, municipalities close to the coast, or surrounding Barcelona, were more likely to present high levels of ignition densities. The ignitions whose origins were smokers (smo), machinery (mac), or electric lines (ele) were found to be located near main transportation routes, whereas ignitions related to agriculture (agr) and lightning (lig) were aggregated in the central area of the region, although they showed a lesser degree of similarity than those previously stated. Finally, ignitions caused by pastures (pas), and forest management operations (for), presented a distinct spatial pattern. In the case of burning pastures, most ignitions tended to be in the northeast of the region, whereas ignitions due to forest work (for) were mainly in the northwest.

Other spatial features could be observed from the results, such as a clear gradient of ignition density levels, especially in the case of less common ignitions, for which the use of larger bandwidths was needed to define the ignition probability densities.

3.2. Socioeconomic Predictors

For the portfolio of socioeconomic variables, the PCA identified six different axes, using the criteria of Eigen values higher than 1 (Table IV). After the data were rotated for a clearer analysis, the axes were named according to the variables that received the highest scores, thus: “population,” “agriculture,” “unemployment,” “recreation,” “cattle,” and “cars.” These six axes explained 74.25% of the total variance.

As described in the methodology, the main axes resulting from the PCA were used to define the combination of factors that might explain the classification of a municipality in a specific ignition level. Crossing the PCA axes by ignition causes resulted in a large number of combinations. Therefore, only the four most common ignition causes were considered for thorough analysis, and the representation of the results included only selected axes.

The pattern of the ignition levels associated with unknown (unk) causes was very similar to the intentional (int) one (Fig. 4). The highest ignition levels were mostly differentiated according to high values of population and settlement-related variables, and to a lesser degree by the presence of forest areas and high unemployment rates.

In the case of causes related to agriculture (agr), the ignition levels were mainly differentiated according to the presence of agricultural land and agricultural machinery, the highest ignition levels being where the agrarian activity was most intense. By contrast, the population patterns did not seem to have an important role in classifying the ignition levels (Fig. 5). An interesting though expected result was that causes related to lightning (lig) usually occurred in untilled areas (i.e., forested ones), with no relation to population patterns or unemployment rates.

When all the ignition causes were plotted together against the PCA axis, it was observed that depending on the cause, the very high ignition levels were located in very different areas (Fig. 6). This meant that the combination of socioeconomic factors used to explain the aggregation of the ignitions on the municipality level was driven by the specific ignition causes for the very high ignition levels. Some
Fig. 2. Levels of ignition density by municipality, for fires intentionally originated, due to agriculture labor, of unknown origin, or caused by lightning, smokers, or electric lines.
clusters were nevertheless observed between causes, one formed by agriculture (agr), pastures (pas), and lightning (lig), a second one formed by the presence of forest work (for) and machinery (mac), and a third and larger one formed by unknown (unk), intentional (int), smokers (smo), campfires (cam), and electric lines (ele).

4. DISCUSSION

The present study analyzes the spatial aggregation patterns of fire ignitions in Catalonia during the period 1995–2008. For this purpose, the data on fire ignitions were segregated according to their specific ignition cause. As expected, the aggregation patterns
of the ignitions varied depending on the ignition causality.\(^{(2–4)}\) The reasons behind not expanding the temporal frame of study with more current fire data were the lack of socioeconomic data from recent censuses, and the changes in the socioeconomic situation of the country after 2008 resulting in potentially large changes in the derived data used as a basis for explanatory variables in the analysis, that could cause distortions in the analysis, and the potential impact of varying conditions due to the 2008 economic crisis.

The methodology used to convert the ignition densities into a municipal-level scale entails a significant loss of spatial variation for the ignition density. For example, it has been demonstrated that factors related to the proximity of infrastructures influence the occurrence of ignitions at smaller scales than administrative borders.\(^{(21)}\) However, the proposed homogenization at administrative levels (municipality) is required to develop a regional-level fire management strategy.\(^{(35)}\) It allows the analysis of the role of different socioeconomic factors influencing the density of ignition level, as the data collected for those factors are usually reported at the municipal level.

The divergences on the allocation of ignition densities according to their cause emphasizes the need to consider each ignition group as independent, in particular when the factors related to its occurrence are to be assessed. The different location of risky areas identified in the spatial analysis provided a basis for rejecting the traditional approach of dividing the ignitions merely into natural or human-caused before analyzing the factors influencing their aggregation pattern. As expected, the spatial variation found in such patterns was linked to a combination of socioeconomic factors, which act as surrogates of the many variables directly related to the occurrence of ignitions. For example, intentional fires and those of unknown origin not only had similar spatial aggregation patterns, but in both cases variables related to “population” concentration and “unemployment” (in the PCA axes) had a strong influence on the ignition occurrence and unemployment rates on the occurrence of ignitions. For example, intentional fires and those of unknown origin not only had similar spatial aggregation patterns, but in both cases variables related to “population” concentration and “unemployment” (in the PCA axes) had a strong influence on the occurrence of ignitions. For example, intentional fires and those of unknown origin not only had similar spatial aggregation patterns, but in both cases variables related to “population” concentration and “unemployment” (in the PCA axes) had a strong influence on the occurrence of ignitions. 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main variables defining an increase in the value of the “population” axis are: housing and population densities, presence of conflicts, hostelling capacity, and population growth. Therefore, the influence of this axis on the identified risk areas agrees with what has been reported in several studies focused on the analysis of the main factors influencing human-caused ignitions.\(^{(18,23,25,41)}\) The tendency of a large number of ignition causes to aggregate similarly, such as those reported above, suggests that they are triggered by similar socioeconomic factors. On the other hand, other ignitions (e.g., caused by rural activities) show a divergence in both the aggregation patterns and the influence of factors underlying their aggregation.

When nonsegregated by causes, those fires originated from agricultural activities, burning of pastures, and, to a lesser extent, related to forest works often produce variations in the trends concerning the factors explaining their occurrence.\(^{(11,42)}\) These types of fires are often better explained by variables such as the intensive use of rural land\(^{(24,41,43,44)}\) that may be negatively correlated to the presence of urban areas and high unemployment rates.\(^{(43,45)}\) In our study, fires of natural origin tend to occur on remote rural areas of medium to high elevation\(^{(11)}\) although their frequency suffers a sharp reduction in the highest areas of the Pyrenees, where fuel humidity can be a limiting factor for fire ignitions.\(^{(46)}\)
Fig. 5. Average values for the causes related to agriculture (agr) and lightning (lig) for the three main axis of the PCA. Numbers represent the ignition levels. Lines represent twice the standard error of the means represented.

The observed variations among ignition causes in terms of location of risk areas, and socioeconomic factors related to the spatial distribution of ignition clusters, underline the need (i) to implement these analyses separately for each ignition cause and (ii) to consider the specific ignition regime and socioeconomic reality of the area or region of study\(^{(10)}\) when defining fire risk prevention strategies. Additionally, the aggregations of fire ignitions not only differ spatially, but often temporally, according to their causes. For example, a preliminary analysis of the seasonality of the ignition occurrence shows that in Catalonia the ignitions of intentional cause, or due to lightning, smokers, electric lines, engines, campfires, and most of the unknown ones, tend to occur during the summer, whereas ignitions caused by rural work such as those linked to agriculture, forest work, and pasture burning tend to occur between January and April.

It can be assumed that a deeper knowledge of the location and timing of fire ignition occurrence, per ignition cause, must translate into more cost-efficient prevention measures that must be oriented to limit the factors favoring ignition occurrence. Such improvement will be based on implementing specific preventive measures depending on the ignition cause, from improving awareness and education in the case of smokers or recreational activities, regulation and practice control in the case of rural work, and law enforcement and vigilance in the case of
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5. CONCLUSIONS

The results confirm the idea that the spatial aggregation patterns of fire ignitions and the factors defining their occurrence are specific for each of the causes of ignition. Intentional fires and those of unknown origin were found to have similar spatial aggregation patterns, suggesting that those of unknown origin are closely related to intentional causes. High ignition density areas are related to population concentration and high unemployment rates. Additionally, fires originated from forest work, agricultural

Fig. 6. Average values for the highest ignition level (5 = very high) according to the causes and selected PCA axis. Lines represent twice the standard error of the means represented.

intentional fires, with specific emphasis on the location of such measures. In addition, the relative importance of these fires of unknown origin (11.4%) and their possible relation with intentional fires should be an incentive for additional efforts on identifying, reporting, and recording causal data for those fires. The application of the findings for implementing prevention strategies could be further improved if it is supplemented with additional research on the conditions that cause an ignition to become a socially damaging fire.
activities, burning of pastures, and lighting have a very specific behavior on their own, differing from the similarities found in the spatial aggregation of ignitions originated from smokers, electric lines, machinery, campfires, and those of intentional or unknown origin.

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REFERENCES

1. Podur J, Martell DL, Csislag F. Spatial patterns of lightning-caused forest fires in Ontario, 1976–1998. Ecological Modelling, 2003; 164:1–20.
2. Prestemon JP, Butry DB. Time to burn: Modeling wildland arson as an autoregressive crime function. Journal of Agricultural Economics, 2005; 87(3):756–770.
3. Genton MG, Butry DT, Gumpertz ML, Prestemon J. Spatio-temporal analysis of wildland fire ignitions in the St Johns River Water Management District, Florida. International Journal of Wildland Fire, 2006; 15:87–97.
4. González-Olabarria JR, Brotons L, Gritten D, Tudela A, Teres JA. Identifying location and causality of fire ignition hotspots in a Mediterranean region. International Journal of Wildland Fire, 2012; 21(7):905–914.
5. Pew KL, Larsen CPS. GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rain forest of Vancouver Island, Canada. Forest Ecology and Management, 2001; 140:1–18.
6. Badia A, Saur D, Cerdan R, Llurdes JC. Causality and management of forest fires in Mediterranean environments: An example from Catalonia. Environmental Hazards, 2002; 4(1):23–32.
7. Amatulli G, Perez-Cabello F, de la Riva J. Mapping lightning/human-caused wildfire occurrences under ignition point location uncertainty. Ecological Modelling, 2007; 200:321–333.
8. Vasconcelos MJ, Silva S, Tomé M, Alvim M, Cardoso Pereira JM. Spatial prediction of fire ignition probabilities: Comparing logistic regression and neural networks. Photogrammetric Engineering and Remote Sensing, 2001; 67:73–81.
9. Yang J, He HS, Shifley SR, Gustafson EJ. Spatial patterns of modern period human-caused wildfire occurrence in the Missouri Ozark highlands. Forest Science, 2007; 53:1–15.
10. Ganteaume A, Camia A, Jappiot M, San-Miguel-Ayanz J, Long-Fournel M, Lampin C. A review of the main driving factors of forest fire ignition over Europe. Environmental Management, 2013; 51(3):651–662.
11. Alexandrian D, Gouriran M. Les incendies de forets en France. Revue Foretirière Française, 1990; XLII, 34–41.
12. Vazquez A, Moreno JM. Sensitivity of fire occurrence to meteorological variables in Mediterranean and Atlantic areas of Spain. Landscape and Urban Planning, 1993; 24:129–142.
13. Wotton BM, Martell DL, Logan KA. Climate change and people-caused forest fire occurrence in Ontario. Climatic Change, 2003; 60:275–295.
14. Butry DT, Pye JM, Prestemon JP. Prescribed fire in the interface: Separating the people from the trees. Pp. 132–136 in Outcalt KW (ed). Proceedings of the Eleventh Biennial Southern Silvicultural Research Conference” General Technical Report GTR-SRS-48, U.S. Department of Agriculture, Forest Service, Southern Research Station, Asheville, NC, 2002.
15. Grala K, Cooke WH. Spatial and temporal characteristics of wildfires in Mississippi, USA. International Journal of Wildland Fire, 2010; 19(1):14–28.
16. Omi PN, Forest Fires: A Reference Handbook. Santa Barbara, CA: ABC-CLIO, 2005.
17. Martell DL, Otukol S, Stocks BJ. A logistic model for predicting daily people-caused forest fire occurrence in Ontario. Canadian Journal of Forest Research, 1987; 17:394–402.
18. Cardille JA, Ventura SJ, Turner MG. Environmental and social factors influencing wildfires in the upper midwest, United States. Ecological Applications, 2001; 11(1):111–127.
19. Vasconcelos MJ, Silva S, Tome M, Alvim M, Pereira JMC. Spatial prediction of fire ignition probabilities: Comparing logistic regression and neural networks. Photogrammetric Engineering and Remote Sensing, 2001; 67(1):73–81.
20. Catry FX, Rego FC, Baçao FL, Moreira F. Modelling and mapping wildfire ignition risk in Portugal. International Journal of Wildland Fire, 2009; 18(8):921–931.
21. González-Olabarria JR, Mola-Yudego B, Pukkala T, Palahi M. Using multi-scale spatial analysis to assess fire ignition density in Catalonia, Spain. Annals of Forest Science, 2011; 68:861–871.
22. Badia-Perninyà A, Pallares-Barbera M. Spatial distribution of ignitions in Mediterranean periurban and rural areas: The case of Catalonia. Journal of Wildland Fire, 2006; 15:187–196.
23. Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB. Human influence on California fire regimes. Ecological Applications, 2007; 17(5):1308–1402.
24. Martínez J, Vega-Garcia C, Chuvieco E. Human-caused wildfire risk rating for prevention planning in Spain. Journal of Environmental Management, 2009; 90(2):1241–1252.
25. Martínez-Fernandez J, Chuvieco E, Koutsisias N. Modelling long-term fire occurrence factors in Spain by accounting for local variations with geographically weighted regression. Natural Hazards and Earth System Sciences, 2013; 13:311–327.
26. Koutsisias N, Kalaboukis KD, Allgöwer B. Fire occurrence patterns at landscape level: Beyond positional accuracy of ignition points with kernel density estimation methods. Natural Resource Modeling, 2004; 17(4):359–375.
27. Rosenblatt M. Remarks on some nonparametric estimates of a density function. Annals of Mathematical Statistics, 1956; 27:832–837.
28. Levine N. CrimeStat II: A Spatial Statistics Program for the Analysis of Crime Incident Locations. Washington, DC: Houston, TX and the National Institute of Justice, 2002.
29. Rowlingson B, Diggle PJ. Splus: Spatial point pattern analysis code in s-plus. Computers & Geosciences, 1993; 19:627–655.
30. Bivand RS, Gebhardt A. Implementing functions for spatial statistical analysis using the R language. Journal of Geographical Systems, 2000; 2(3):307–317.
31. Diggle PJ. A kernel method for smoothing point process data. Journal of Applied Statistics, 1985; 34:136–147.
32. Berman M, Diggle P. Estimating weighted integrals of the second-order intensity of a spatial point process. Journal of the Royal Statistical Society. Series B, 1989; 5:81–92.
33. Silverman BW. Density Estimation for Statistics and Data Analysis. London, UK: Chapman and Hall, 1986.
34. Worton BJ. A convex hull-based estimator of home-range size. Biometrics, 1995; 51:1206–1215.
35. de la Riva J, Pérez-Cabello F, Lana-Renault N, Koutsias N. Mapping wildfire occurrence at regional scale. Remote Sensing of Environment, 2004; 92:288–294.
36. Prestemon JP, Pye JM, Butry DT, Holmes TP, Mercer DE. Understanding broad-scale wildfire risks in a human-dominated landscape. Forest Science, 2002; 48:685–693.
37. Velez R. La prevención. In García-Brage A (ed). La Defensa Contra Incendios Forestales Fundamentos y Experiencias. Madrid: McGraw-Hill/Interamericana de España, 2000.
38. Catry FX, Damasceno P, Silva JS, Galante M, Moreira F. Spatial distribution patterns of wildfire ignitions in Portugal. Modelação espacial do risco de ignição em Portugal Continental, 2007; 8.
39. Sebastián-López A, Salvador-Civil R, Gonzalo-Jimenez J, San-Miguel-Ayanz J. Integration of socio-economic and environmental variables for modelling long-term fire danger in southern Europe. European Journal of Forest Research, 2008; 127:149–163.
40. Archibald S, Roy DP, van Wilgen BW, Scholes RJ. What limits fire? An examination of drivers of burnt area in southern Africa. Global Change Biology, 2009; 15:613–630.
41. Romero-Calcerrada R, Novillo CJ, Millington JDA, Gomez-Jimenez I. GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (central Spain). Landscape Ecology, 2008; 23:341–354.
42. Miranda BR, Sturtevant BR, Stewart SI, Hammer RB. Spatial and temporal drivers of wildfire occurrence in the context of rural development in northern Wisconsin, USA. International Journal of Wildland Fire, 2012; 21:141–154.
43. Vigilante T, Bowman DMJS, Fisher R, Russell-Smith J, Yates C. Contemporary landscape burning patterns in the far North Kimberley region of north-west Australia: Human influences and environmental determinants. Journal of Biogeography, 2004; 1:1317–1333.
44. Ricotta C, Guglietta D, Migliozzi A. No evidence of increased fire risk due to agricultural land abandonment in Sardinia (Italy). Natural Hazards and Earth System Sciences, 2012; 12:1333–1336.
45. Dickson BG, Prather JW, Xu Y, Hampton HM, Aumack EN, Sisk TD. Mapping the probability of large fire occurrence in northern Arizona. USA. Landscape Ecology, 2006; 2:747–761.
46. González JR, Palahi M, Trasobares A, Pukkala T. A fire probability model for forest stands in Catalonia (north-east Spain). Annals of Forest Science, 2006; 63:169–176.
47. National Association of State Fire Marshals Fire Research and Education Foundation. Conquering the “Unknowns” Research and Recommendations on the Chronic Problem of Undetermined and Missing Data in the Causal Factors Sections of the National Fire Incident Reporting System. U.S. Federal Emergency Management Agency, 2011.