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Statistical analysis of fire frequency models for Catalonia (NE Spain, 1975–1998) based on fire scar maps from Landsat MSS data

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Abstract. This paper estimates fire frequency in Catalonia (NE Spain) for the last quarter of the 20th Century (1975–1998) from historical burned area maps. Remote sensing images provided perimeters of fires ≥30 ha, which were used to characterize the temporal patterns of fire occurrence in Catalonia. Several fire frequency models were used to reproduce the observed pattern of wildfires occurrence in the study period. Natural fire rotation period was estimated to be 133 years. Poisson tests were carried out to check random fire occurrence either along the time period or across the analysed region. Observed fires were not randomly generated either in space or in time, despite being sampled using two different plot sizes. This sampling design was also used for Mean Fire Interval (MFI) analysis, which allowed us to significantly fit a Weibull distribution to the observed proportion of fire intervals (for both sample sizes), enabling us to estimate the hazard of burning, mortality, and survivorship functions. Finally, MFI was also applied to forest regions of Catalonia, which are defined according to forest management plans based on their homogeneous climatic conditions. Such an analysis revealed relevant differences in forest management and their consequences on fire occurrence.

Introduction

The term fire regime, defined in the middle 1970s, integrates several concepts related to temporal and spatial patterns of fire occurrence in a particular area and the ecological effects of such disturbances. Since proposed by Gill (1975), the term fire regime has been used as a framework to plan experimental studies in order to describe interactions between fire and vegetation or to formulate land management plans (Fox and Fox 1987; Trabaud 1987; Russell-Smith *et al*. 1998). Gill proposed four main components characterizing fire regimes: intensity, extent, frequency and seasonality. Fire intensity and extent define spatial patterns of fire occurrence while the other two components aid interpretation of temporal patterns. Fire intensity is determined mainly by the maximum temperature reached at the fire front and the residence time of flames (Pérez and Moreno 1998). It is specific to each wildfire and fuel-type burned, and is related to fire severity (the observed effect on plants). It determines the degree of damage caused by fire, and consequently the effects on the ability of plants and animals to recover (Retana 1996). Fire extent is a relevant factor in the regeneration processes. Plant species that regenerate after fire from seeds (in the canopy or soil) might decrease their abundance if such a strategy is limited by fire severity and by dispersal from individuals surviving outside the fire perimeter. Fire frequency characterizes fire regimes at the medium and long term, mainly because fire recurrence greatly affects plant survival probability by determining the time available for individual plants to reach maturity. Finally, the season of fire occurrence leads to differences in physiological plant status, seed bank load and fire intensity (Trabaud 1987). Therefore, plant response to fire by resprouting and germination is heavily influenced by the seasonality of fires.

Several authors have emphasized additional factors that can affect the temporal patterns of fire occurrence. Among those, Fox and Fox (1987) suggested fire interval, fire period and fire history. Fire interval is associated with fire frequency and represents the elapsed time between two fires in a geographic location. Fire period is the inverse of fire frequency, i.e. the length of time required for an area the size of the study area to burn (equivalent to fire cycle *sensu* Johnson and Gutsell 1994). Finally, fire history summarizes to a greater extent fire occurrence in a place and is defined as the presence or absence of certain plant species in the plant community or by the degree of their population growth. It seems that these

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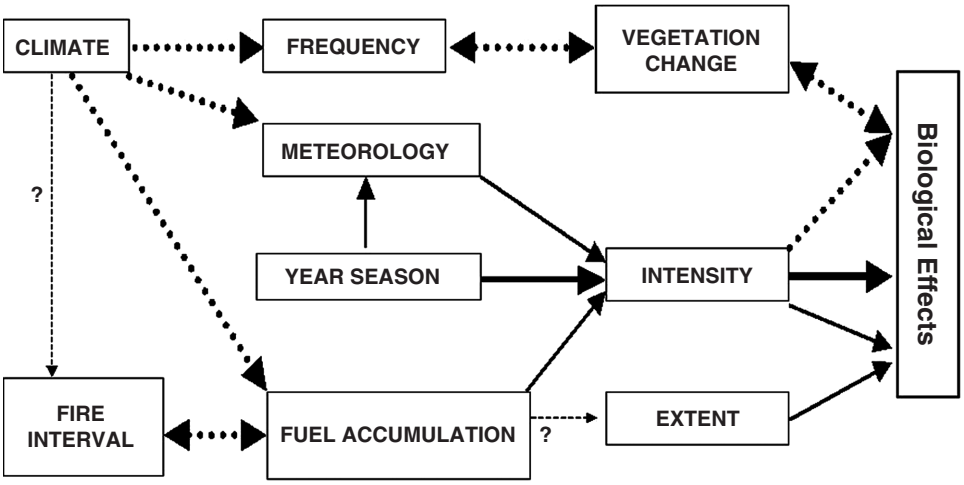

Fig. 1. Complex interactions among the different elements of the fire regime. Modified from Fox and Fox (1987). Question marks represent relationships not yet clarified.

recent contributions are rather components of fire frequency. The role of fire frequency and its interaction with the rest of the elements of the fire regime (Fig. 1) is mainly based on the accumulation of fuel through time.

Fire frequency measurements have been traditionally carried out by using different techniques such as tree ring scars, charcoal soil rests, palynological studies and fossil macrorests from the bottoms of lakes, aerial photointerpretation, and reconstruction of forest-stand replacement after fire. The two main approaches to fire history are analysis of point frequencies and area frequencies. Point frequencies assess fire occurrence at one location, while area frequencies assess fire occurrence at the scale of the landscape. Although both approaches yield a fire frequency estimate, they represent different types of information because of the difference in scale. Selecting the appropriate method depends primarily on the vegetation types and the physical features of the study area. In this paper all the estimates are given as area frequencies.

The goal of this paper is to estimate fire frequency in Catalonia for the last quarter of a century (1975–1998) from historical data of burned area maps. This work was motivated by the lack of detailed studies on the temporal patterns of fire occurrence in the Mediterranean basin. For instance, no results have been reported on the hazard of burning in the study area. Catalonia is located in the Mediterranean basin, where fire frequency has significantly increased over the last four decades. This trend is opposed to the reported decrease in fire frequency in boreal forests (Kasischke and Stocks 2000). We also estimated Mean Fire Interval for the forest regions in our study area. Forest management plans in Catalonia have divided the whole territory into eight forest regions (Plá General de Política Forestal, DGMN 1994). Each forest region is ecologically and climatically homogeneous (Fig. 2). In addition, each forest region has a similar extent but a different percentage of forested area and they have been distinctly affected by wildfires in the last 24 years.

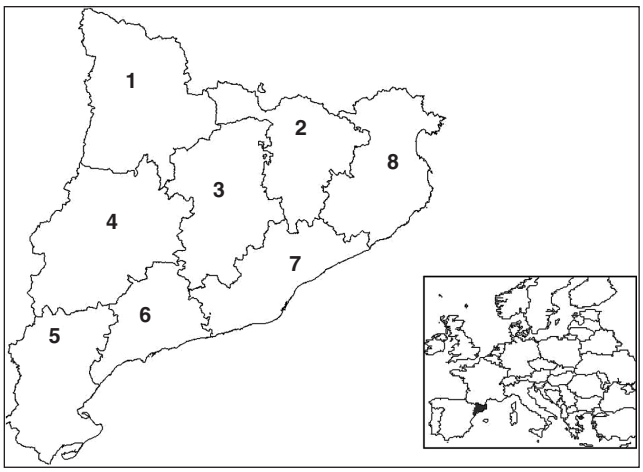

Fig. 2. Catalonia in the European context and its forest regions.

Study area

The study region (Catalonia) covers an area of around 32 100 km^2 in the north-east of the Iberian Peninsula, beside the Mediterranean Sea (Fig. 2). Shrublands and forests cover ~60% of this region. Agricultural lands cover most of the remainder, contributing to the fragmentation of natural vegetation. The majority of the study area has a Mediterranean climate, with moist, mild winters and dry, hot summers (Clavero *et al*. 1997), which favor wildfires. The region is typical of fire-prone ecosystems and many species have a recognized ability to regenerate after fire (Trabaud 1987). In the last decades, fire occurrence has increased in this region as a consequence of land use changes and increasing climatic fire risk (Piñol *et al*. 1998; Díaz-Delgado and Pons 2001).

Methods

Fire scar maps

In order to produce the fire occurrence map, a long time series of Landsat MSS images (100) for the 1975–1993 period, covering 90% of the study area, was acquired. After applying geometrical and radiometrical corrections, fire scars greater than 0.3 km^2 were detected as differences in the subtraction values between two consecutive NDVI images. Thresholds to these differences were established from empirical regression models based on 21 fires (for more details on methods see Salvador *et al*. 2000). This procedure allows recognition of areas that have burned more than once during the study period. Therefore, the fire scar maps obtained were converted from raster to vector GIS structured format to enable spatial analysis and database query. For every fire, a date of occurrence was assigned in addition to other relevant variables, such as burned area and fire perimeter. Although raster format has been successfully used by Wells and McKinsey (1990) in Southern California, vector format has the advantage of its structural hierarchy (Maffini 1987; Minnich and Chou 1997). The vector format of the fire database also enables one to retain fire recurrence (number of fires along the period) in any geographical point by multiple records (the same element is linked to several registers, Date 1995).

Ancillary thematic maps were used to complete the initial fire history database (covering the 1975–1993 period, Díaz-Delgado *et al*. 2002) that enabled the updating of the fire history up to 1998 (24 years). The ancillary maps were the Forest Fire Map of Catalonia (1986–1990 and 1994–1998), the CORINE Land-Use-Land-Cover map (1991) and the Land Use Cover Maps of Catalonia of 1987 and 1992.

Fire frequency models

Several fire frequency models have been proposed based on available sampling techniques. Since the beginnings of the 1980s, remote sensing images have been employed to discriminate historical fire perimeters of burned areas and this has allowed a reconstruction of fire history and a characterization of fire regimes (Minnich 1983; Press 1988). Several fire frequency models have been applied to the data supplied by remote sensing images. Below (Fig. 3), we introduce the three fire frequency models used in this paper; namely, Natural Fire Rotation Period (NFR), Poisson Process Model (PPM) and Mean Fire Interval (MFI).

Natural Fire Rotation Period (NFR)

NFR was initially proposed by Heinselman (1973) and subsequently used by Agee (1993) and Heyerdahl and Agee (1996). It is a simple approach aimed at knowing how many years are necessary to burn an area of a similar extent to the study area. It may be estimated according to:

$$NFR = N/(A/S),$$

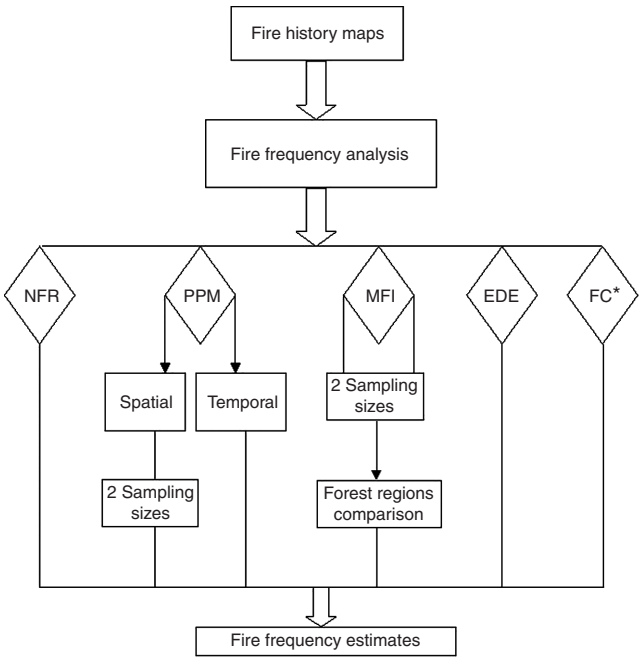

Fig. 3. Flowchart of the different methods used to estimate fire frequency. See text for more details. (*) Fire Cycle has not been used in this work.

where N = number of years in the period, A = total area burned, and S = the size of the study area.

This approach has several advantages such as, it does not depend on any fire frequency model and thus requires none of the assumptions about stationarity of the process (where the mean, variance and autocorrelation structure do not change over time) or homogenous spatio-temporal regions made by some of the other methods. The method is also relatively simple, and thus fairly easy to understand. Since the method fully reconstructs the size of fires and their distribution in space and time, it more accurately represents the spatial and temporal variability in the fire regime. Nevertheless, the method suffers from the following limitations:

- A significant bias and/or misinterpretation may result if the burned surface of all fires is not accurately determined for the period of study;
- The lack of a formal statistical model makes hypothesis testing difficult; and
- It is difficult to use this method to formally test hypotheses (e.g. about fire–climate relations, or differences in fire frequency between two regions or time periods).

Poisson Process Model (PPM)

A random process with independent events, such as fire occurrence (in space and time), can be fitted to a Poisson distribution according to:

$$p(x) = \frac{e^{-\lambda} * \lambda^{x}}{x!},$$

where $p(x)$ is the probability of fire occurrence and λ represents the mean number of fires per time interval or unit area. Goodness of fit can be easily checked in both tests: temporal and spatial. For the latter, a stratified random sampling was employed. The study area is divided in orthogonal matrices and random locations are chosen for every matrix (Eastman 1992). This sort of sampling combines a quite appropriate spatial cover with a low risk of bias.

Due to the relevance of the spatial scale on the Poisson test, we carried out two samplings with different sample size. First, we selected 34 plots from a total of 60 distributed across the landscape (random sampling for raster images yield points located in the sea that were discarded). Every point was buffered in a radius of 5 km ($\sim$78.55 km^2 per area and a total area sampled of 2670.7 km^2). The second sampling process selected 272 areas from 500. A radius of 1581 m was employed to buffer each point generating 7.85 km^2 areas (10 times smaller than the first sampling) covering 2136.56 km^2. Such circular plots were overlain with the fire history database (1975–1998). Each fire occurrence inside sample areas was thus recorded and analysed. The random process assumes that:

- Climate and local conditions are uniform in the study area through the analysed time period;
- Fire ignitions are randomly distributed through time and occur randomly over the whole study area; and
- The number of fires per study period is independent of the number of fires in the previous time period. For the spatial analysis, the number of fires at any location is independent of the number of fires at any other.

These three assumptions are clearly not valid and therefore inferences from the analysis have to be made with caution.

Although the model yields useful results, even though not achieving all the premises, the magnitude of the introduced error linked to fact that we are usually far from the premises, is still unknown. For instance, there is a high spatial correlation in fire occurrence due to the increase of fire hazard in locations adjacent to burning areas. However, in certain cases we may correctly fit a Poisson function to the spatial model (Agee 1993).

Among the advantages, we find that PPM is relatively simple and easy to understand. They have been fitted to several databases. Test of hypothesis can be easily applied, and allows one to differentiate spatio-temporal regions with significantly distinct fire frequencies. Among the caveats, we find that fire records are usually hard to be fitted to the temporal model in a unique point (unless data come from fire scar sampling on trees). This is why study areas are usually employed. Therefore, results from applying PPM cannot be considered as a correct estimate of fire frequency in any given point of the study area. A PPM for spatial patterns assumes that the whole study area presents a homogeneous fire frequency. Sampling areas are then considered as replicates, which it is extremely hard to test. Finally, the Poisson model does not allow a complete interpretation, since it does not describe survivorship, mortality or fire risk functions, which are characteristics of fire frequency models.

Mean Fire Interval (MFI)

In order to avoid shortcomings of the Poisson model, several authors (Arno and Sneck 1977; Kilgore and Taylor 1979; Agee 1993) proposed an alternative approach: the Mean Fire Interval model. It is based on estimates of the mean time interval between fires at any location of the study area. From every random sampling point mentioned before, we extracted fire occurrences and fire intervals, for the spatial PPM. Interval sizes were encountered and interval proportions of every different size were extracted. We did not account for interval areas where only one fire occurred.

The density function $f(t)$ represents the probability of finding a fire interval of size t according to:

$$f(t) = [(c * t^{c-1})/b^c] * \exp[-(t/b)^c],$$

where c is the shape parameter, b the scale parameter, and t is the duration of the interval considered (Johnson and Gutsell 1994). The parameters c and b are calculated by using the following equations:

$$c = 1/[[\Sigma(x_i^c * \ln x_j)/\Sigma x_i^c] - (\Sigma \ln x_j/N)]$$
$$b = [\Sigma x_i^c/N]^{1/c},$$

where $x_i (i = 1, N)$ is the ith fire interval and N is the total number of observed intervals (see more details on methods in Johnson and Gutsell 1994). To estimate c, it is necessary to make an iterated fitting that will minimize differences from an initial value.

If the PPM is significantly fitted to fire occurrence through time, the number of fires of every time period is considered independent. Then, the fire interval distribution is supposed to be well suited by a negative exponential function (a special case of the Weibull function where $c = 1$). The parameter b of the negative exponential function will determine the mean fire interval.

Fire events that are independent neither spatially nor temporally imply that c is determined by fire hazard $\lambda(t)$ and not necessarily linked to fire hazard due to fuel accumulation (Johnson and Gutsell 1994), which increases as forest stand age does. Then $\lambda(t)$ informs about fire probability in an area or, in other words, about the tight relationship between mortality and forest stand age. $\lambda(t)$ is calculated as follows:

$$\lambda(t) = c * t^{c-1}/b^c.$$

Such a fire hazard gives an increasing mortality rate that, once accumulated, will produce fire occurrence probability as a function of the elapsed time from the last wildfire. Consequently, both curves, mortality curve $F(t)$ and survivorship

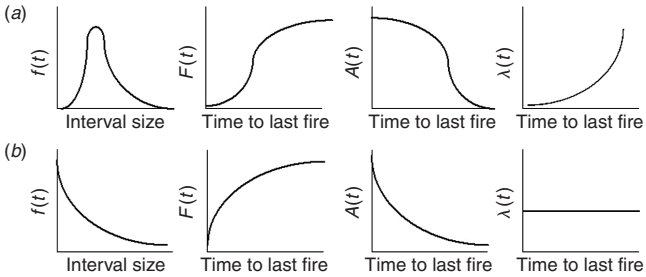

Fig. 4. Characteristic functions of fire frequency models. Notice the differences between the two methods (*a*, Weibull and *b*, negative exponential) fitted to the empirical observations. $f(t)$ is the Fire Interval Distribution, $F(t)$ is the Cumulative Mortality Distribution, $A(t)$ is the Time-Since-Fire Distribution, and $\lambda(t)$ is the Hazard of Burning Function.

curve $A(t)$ may be theoretically estimated as follows:

$$F(t) = 1 - \exp[-(t/b)^c]$$
$$A(t) = \exp[-(t/b)^c].$$

$F(t)$ and $A(t)$ are reciprocal and are empirically obtained from the curve of proportion of fire intervals. $F(t)$ indicates the probability of finding a fire interval smaller than or equal to t years. $A(t)$ represents the probability of finding a fire interval greater than or equal to t years. In fact, $\lambda(t)$ may be calculated as follows:

$$\lambda(t) = f(t)/A(t).$$

In Fig. 4 we can appreciate the differences in fire frequency functions according to the adjusted function: Weibull or negative exponential.

MFI assumes several premises such as:

- Fire records have to be similar for every sampling area;
- The model based on the Weibull distribution assumes different flammability for every forest stand just determined by stand-age, and thus ignitions will occur randomly; and
- A negative exponential distribution assumes the same flammability for every forest stand, independently of stand age; ignitions will also occur randomly.

The main advantage of this method is that it works directly with a series of fire dates at each location. This has several important implications:

- The researcher is able to fit the fire interval distribution (from the fire frequency model) directly to the data, making modeling and model interpretation fairly straight forward;
- Fire frequency can be computed for small areas; and
- The data provide both spatial and temporal resolution on the fire frequency. Thus, changes in fire frequency over time, or differences in fire frequency between two locations, may easily be tested.

However, the MFI suffers from the following limitations:

- The models require a large fire interval dataset, with multiple events recorded at each sample location; and
- A significant bias and/or misinterpretation may result if not all fire dates at a site are discovered. Thus, there will be a tendency to underestimate fire frequency, and this tendency will increase with the length of the period.

Fire frequency estimated by MFI will also increase with area (Kilgore and Taylor 1979). The estimate of fire frequency will no longer be the so-called 'point fire frequency' but the 'fire recurrence interval' (Agee 1993). This is the first link between fire frequency and the sampling spatial unit.

Other fire frequency models

Recently, other methods besides MFI model have been proposed:

- The Fire Cycle approach (Van Wagner 1978; Agee 1993; Johnson and Gutsell 1994) uses mainly the negative exponential function to fit the empirical survivorship curve $A(t)$. It starts by reconstructing the empirical density function for the percentage of area burned against time-since-fire (as shown in Fig. 13). The reciprocal value of the slope from the fitting model (b) is at the same time the rotation period, the MFI (mean forest stand age), and the annual percentage of burned area in the study region (annual probability of any location in the study area to burn). We estimated the b value to be about 105 years. This method is based on the time-since-fire map, which is usually drawn indirectly from forest stand ages maps (Van Wagner 1978). Therefore in these studies, such data are well known previously for the whole study area. Unfortunately, this is not the case for Catalonia, where no data are available before 1975. Moreover, all these works point out the relevant and abrupt changes in slope values along the analysed centuries. These changes in slope are due to climatic and human factors (Johnson and Larsen 1991; Baker 1992; Swetnam 1993; Yin 1993). Very recently, Reed *et al.* (1997) have reexamined this method and introduced a way to estimate the confidence intervals of the density functions extracted from the model. Thus, the goodness-of-fit can easily be assessed. The use of a contagion index to determine the degree of spatial correlation in fire occurrence may help to avoid the inherent bias by autocorrelation in spatial fire occurrence. This approach was not used in this work.
- The analysis of Extreme Disturbance Events (EDE) (Moritz 1997) is a very interesting approach that uses only data from the largest fire of every year along the study period. This method has been proposed at the moment when a scientific controversy was generated on fire suppression policies practised in North America. Thus, several authors assert that such a policy promotes still larger fires

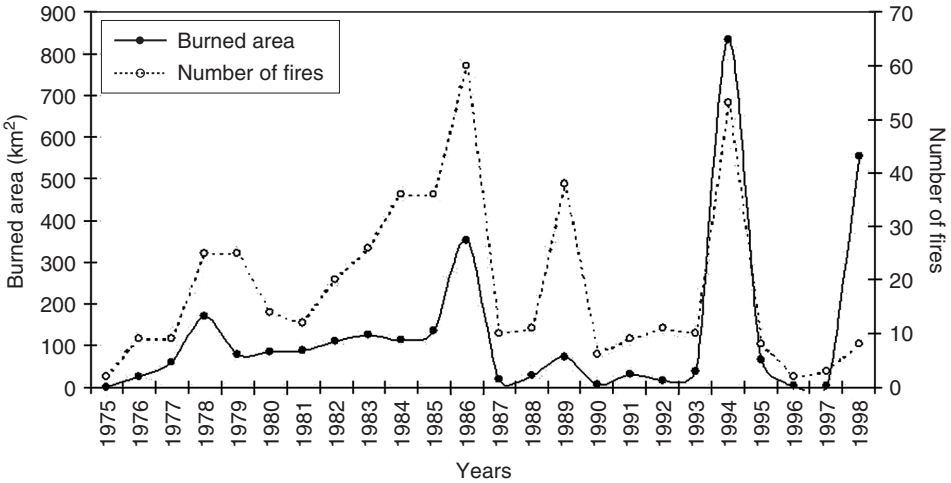

Fig. 5. Number of fires and burned area occurred in Catalonia from 1975 to 1998.

(Oberle 1969; Minnich 1983; Strauss *et al*. 1989; Chou *et al*. 1993; Keeley *et al*. 1999). Large fires that occurred in the study area were analysed following this approach.

Results

We applied four of the five methods of fire frequency analyses proposed to the fire history database of Catalonia for the 1975–1998 period (Fig. 3). A total number of 443 wildfires larger than 0.3 km^2 took place in this period. The total area burned was 16 732.44 km^2. Results on each method are reported below.

Natural Fire Rotation Period

Along the whole study period, the years with the highest number of fires were 1986 (60) and 1994 (53). The years with the largest fire sizes were 1994 (834.26 km^2) and 1998 (552.42 km^2), both affected by wildfires larger than 200 km^2 (Fig. 5). We found a significant correlation between the number of fires and the annual burned area ($r = 0.6$, $P < 0.05$, $n = 24$).

The estimated NFR is 133 years. This value is equivalent to the mean fire interval for any point inside the study area. The reciprocal value, 0.0075, is the mean proportion of burned area per year (0.75%). It also indicates the mean fire probability in any point of the study area, i.e. the point fire frequency. This measure is time scale dependent, i.e. if we estimate the NFR for a different time period, the final value will be greatly different.

Poisson Process Model (PPM)

Temporal analysis

We used a year as the temporal unit for the analysis. The estimated λ value is 18.45 fires per year. We fitted Poisson Distribution (PD) parameters by means of maximum likelihood estimate (MLE). A χ^2 test allowed us to reject the null hypothesis, i.e. that the number of fires per year does not follow a Poisson process ($\chi^2 > 100$, $P < 0.01$). The number of fires per year is not independent from year to year. Figure 6 shows the predicted and observed distribution of fires per year.

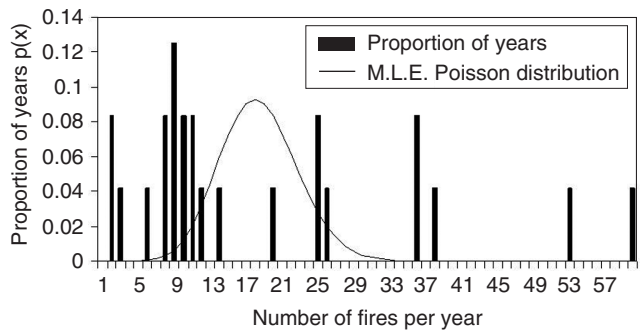

Fig. 6. Predicted (MLE of PD) and observed distribution of fires per year.

Spatial analysis

The largest sampling plots (78.55 km^2) show an average forested area of 52% and the smallest (7.855 km^2) is about 54%. For both cases, the null hypothesis was rejected as interpreted from the χ^2 test on the fit of Poisson distribution (Figs 7 and 8). In other words, the spatial occurrence of wildfires did not fit a random process (large sampling: 34 plots of 78.55 km^2, $\chi^2 = 14.19$, $P < 0.01$; small sampling: 272 plots of 7.85 km^2, $\chi^2 = 17.73$, $P < 0.01$). Results were the same for both samples. In addition, the correlation coefficients between the number of fires and the forested area for each sample show a relevant independence between both variables (large sampling, $r = 0.1$, $P = 0.53$; small sampling, $r = 0.26$, $P < 0.01$). For the largest plots the λ estimated value was 1.93 and for the second sampling $\lambda = 1.71$. Both correspond to mean annual expected values for the total area sampled by

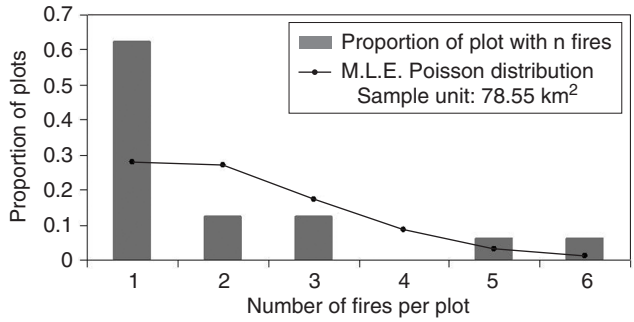

Fig. 7. MLE of a PD for proportion of plots against the number of fires per plot in the first sampling process ($n = 34$ plots).

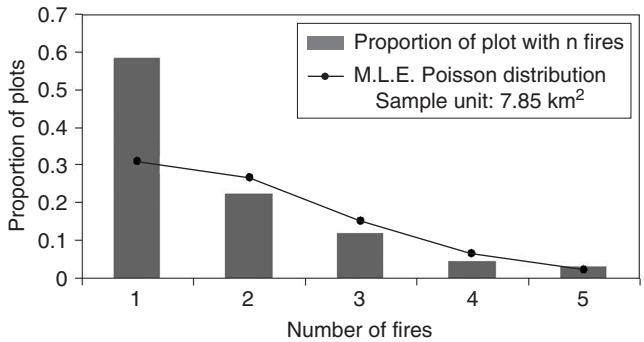

Fig. 8. MLE of a PD for proportion of plots against the number of fires per plot in the second sampling process ($n = 272$ plots).

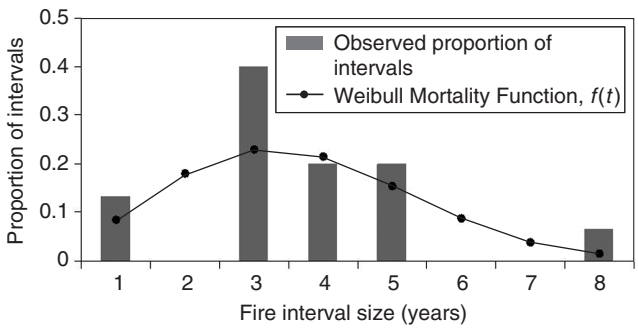

Fig. 9. Frequency distribution of intervals since last fire. Histogram represents empirical data. Dots represent the prediction by a Weibull Mortality Function (large samples, 78.55 km^2).

each sampling size, i.e. 12.09 fires per year for the largest plots and 13.39 for the smallest plots.

Mean Fire Interval

We found a unique mode in the fire interval distribution for both sampling sizes. The observed proportion of fire intervals was fitted in both cases to a Weibull distribution (Fig. 9 and Fig. 10; large plots, $\chi^2 = 10.43$, $P = 0.10$; and small plots, $\chi^2 = 19.07$, $P = 0.32$). Such a distribution is known as the

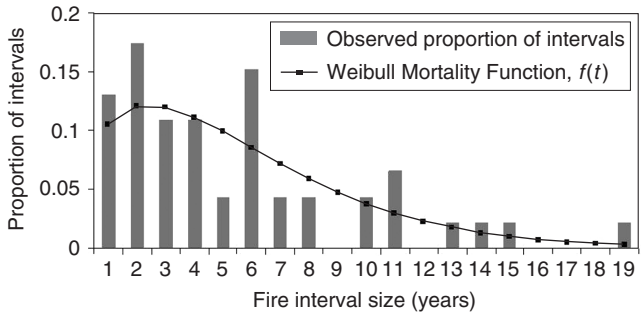

Fig. 10. Frequency distribution of intervals since last fire. Histogram represents empirical data. Dots represent the prediction by a Weibull Mortality Function (small samples, 7.85 km^2).

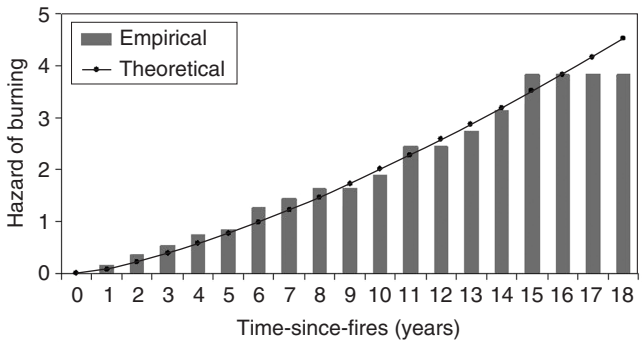

Fig. 11. Cumulative curve of hazard of burning function against time-since-fire. Estimated from data with sample size of 272 plots (7.85 km^2).

Mortality Function, $f(t)$, which gives the probability of fire occurrence in a time interval of t years.

Mean fire interval values are 3.6 and 5.5 for large and small plots respectively. Such values indicate the average number of years between two fires for the total area accounted for in the study. They also represent the time needed to burn an area equivalent to the total area sampled in each case (fire cycle or rotation period), which varies between 23 and 42 years, respectively. These values reveal the average percentage of burned area per year (between 2% and 4%) respectively.

The cumulative hazard of burning, mortality and survivorship curves (both observed and predicted) are plotted *v.* time-since-fire in Figs 11–13. Plots use data from the second sampling method (small samples).

Figure 11 shows how cumulative hazard of burning increases with time since the last fire (fire interval). There is a good correspondence between the theoretical and empirical distributions, except for the last period starting from 15–16 years since the last fire. At this point the hazard of burning becomes quite constant (forest stands older than 15–16 years maintain a similar fire hazard to stands 15–16 years old).

The accumulated mortality (Fig. 12) and survivorship (Fig. 13) curves indicate the probability of fire occurrence and non-occurrence (absence), respectively, according to the time elapsed since the last fire. They are both reciprocal

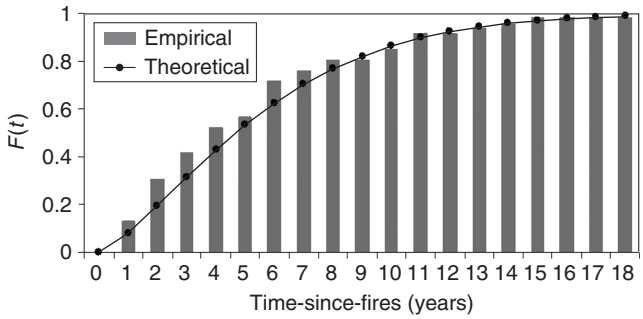

Fig. 12. Cumulative curve of hazard of mortality $F(t)$ *v.* time-since-fire. Estimated from data with sample size of 272 plots (7.85 km^2).

Fig. 13. Cumulative curve of hazard of survivorship $A(t)$ *v.* time-since-fire. Estimated from data with sample size of 272 plots (7.85 km^2).

Table 1. Estimated MFI values for each of the eight forest regions (FR) of Catalonia

MFI values were calculated according to the total forested area of each region. Maximum fire interval, total number of intervals, FR extent and percentage of forested area are also shown for all the FRs

FR	MFI (years)	Longer interval (years)	No. of intervals	FR extent (km^2)	% forest area
1	2.11	4	9	5231.65	89.03
2	2.71	7	7	3481.60	48.16
3	1.20	3	15	3890.16	53.69
4	1.44	4	16	4350.81	70.65
5	1.19	2	16	3236.80	53.34
6	1.10	2	20	2497.85	46.26
7	1.22	3	18	3806.70	48.59
8	1.33	3	15	5585.85	32.91

curves; in our study case we found that 80% of the study area burned starting from the 8th year since the last fire. This is a non-consistent result since fire occurrence in our study area is more frequent than expected under natural fire regimes.

MFI by forest region

MFI can easily be calculated for different regions in order to compare the estimated values that will allow confronting fire regimes and discerning possible causes of differences. Therefore, we estimated MFI for every forest region (Table 1). Regions 5, 6, 7 and 8 are located on the coast where a high human pressure exists and temperatures are buffered by the sea's influence. Region 4 is largely continental with the highest summer temperatures and the lowest percentage of forested region. Regions 1, 2 and 3 are the most mountainous with the lowest mean temperatures, the highest mean precipitation values and the largest forested area.

One of the coastal forest regions, region No. 6, shows the highest estimate of fire frequency in Catalonia. In this region, for the 20 fire intervals sampled in the last quarter of the century, only two fire intervals were longer than 1 year. In other words, wildfires exceeding 0.3 km^2, as analysed in here, took place almost every year, although the percentage of forested area in this region is lower than the average percentage of all the forest regions. This reveals a null or small interaction between fire recurrence and percentage of forested area. However, this coastal region is also the smallest region in extent, which might bias MFI estimates. Despite this possible bias, the correlation between MFI values and forest region extent is not significant ($r = 0.17$, $P = 0.66$).

On the other hand, the most mountainous and forested area (FR #2), located at the central Pyrenees Mountain, has the smaller fire frequency estimate with fire intervals up to 7 years.

Other fire frequency methods: analysis of Extreme Disturbance Events

In only 6 out of the 24 years analysed, the single largest wildfire created a burning area larger than 50% of the total (Fig. 14). Interestingly enough, we do not find any of the three largest fires of the whole time series burning more than 50% of the total burned area (1986, 1994 or 1998). Anyway, the average annual percentage of burned area by the largest fire is ~40%. This value should be considered in future fire management plans.

Discussion and major conclusions

Our work has enabled us to explore the temporal patterns of fire occurrence in Catalonia. Our analysis has also made possible a comparison of the fire regimes of the different forest regions in our study area.

The NFR approach reveals appropriately the fire frequency of the study area. A fire interval of 133 years is expected for most of the study area. Nevertheless, as the NFR is a valid value for any point of the study area, it also indicates the probability of finding a forest stand ≥133 years. On the other hand, the NFR value is also an index of the period necessary to burn an area equivalent to the study area. In our case, only 14% of the study area has been burned in the last 24 years. In addition, fire recurrence analysis shows that 12% of the total burned area was re-burned. This value enhances the role played by spatial recurrence in our study area.

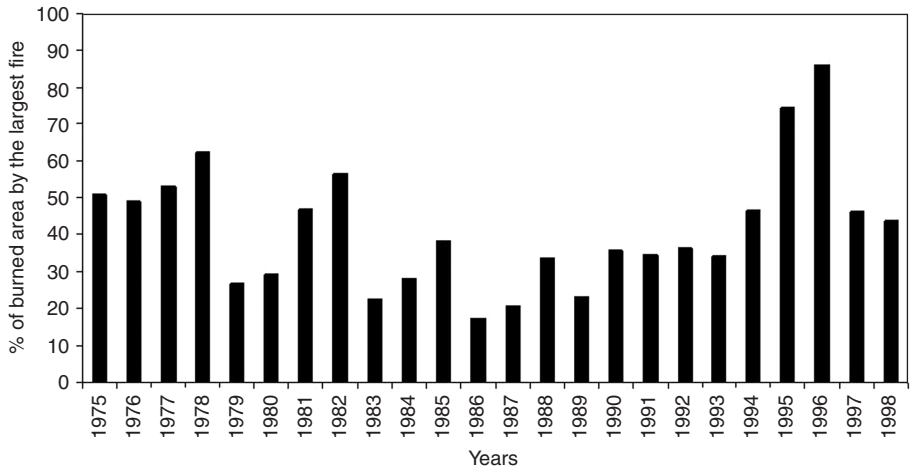

Fig. 14. Annual percentage of burned area by the largest fire according to the EDE analysis.

We found a significant and positive relationship between the number of fires and the total burned area (Fig. 5). Correlation could be explained by the fact that only burned areas larger than 0.3 km^2 were analysed. However, a revision of the administrative fire history database for the 1983–1997 period shows that 95% of the fires were under this size and only contributed up to 7% of the total burned area.

Our results show that fire events are not independent among each other. Such evidence confirms the stationarity (*sensu* Minnich and Chou 1997) of this phenomenon in the study area (Fig. 5) that links fire occurrence to concrete periods (years) and areas. To some extent, this is due to the fact that the percentage of natural ignitions is too low in the fire database (about 5%, Vázquez and Moreno 1998). Human causes, either intentional or due to negligence, contribute to the rest of the wildfire occurrences. Furthermore, the long and usual drought periods in the Mediterranean basin contribute to a higher fire occurrence during dry years. The high variability between years in weather conditions with few days of extreme dry conditions favors the concentration of wildfires in a short period of time. In addition, spatial fuel distribution, fire policy and human pressure are some of the causes of fire occurrence. They play a crucial role in extracting sensible interpretations of spatial fire occurrence (Whelan 1995).

As a consequence of the results, the fire interval distribution is the best way to estimate the MFI and associated functions. In addition, the fitting to the Weibull distribution has been shown as the most appropriate, in particular due to the *a posteriori* assumption that was confirmed: the ignition risk increases with forest stand age. Therefore, our results show for the two different spatial scales an acceptable goodness-of-fit to the Weibull distribution and a constant MFI estimate around the same order of magnitude for both scales: 23–42 years. Such values fall into the observed estimates in other Mediterranean ecosystems (20–50 years according to Chandler *et al*. 1983) and are still more precise than the NFR value. Our results suggest that the hazard of burning increases until reaching a plateau for 15–16-year-old forest stands. This trend departs from the theoretical distribution (Fig. 11). Certain plant communities dominated by conifers with a rapid growth, as in the case of *Pinus halepensis*, may be developed enough after such a fire interval to undergo a new fire irrespective of the continuous and constant increase in fuel load. Even several shrubs with this age are very prone to burning due to an elevated fuel load and a horizontal continuity of the fuel, among other factors (Pla and Rodà 1999).

Although certain authors have stressed the relevance of the extent of the study area to estimate MFI (Kilgore and Taylor 1979; Agee 1993), we have only confirmed changes in the MFI values of the same order of magnitude (23–42 years). We did not observe any effect of this caveat on the sort of fire frequency model better fitted to the observed data. Differences found in MFI values manifest the distinct fire regimes affecting the forest regions.

Other relevant issues related to methods rise from our results:

- On the one hand, our study points out the necessity of employing valid criteria when dividing the study area into several regions in order to be compared. Effective criteria can be the forest policies as in our case, fire-fighting management plans, climatic variability, landscape homogeneity, etc.
- On the other hand, these approaches are strongly encouraged to be applied in fire regimes comparison among different study areas.

Finally, it is worth saying that remote sensing is an excellent ancillary data source on fire history reconstruction. However, we feel that it is time to reinforce the use of this tool by adding new definitions and concepts that allow the correct interpretation of results. In other words, we suggest

to clearly define spatial fire recurrence. Fire frequency has traditionally been estimated for an area. The pursued 'point fire frequency' has been based on tree rings analysis. According to this technique, fire history reconstruction may lead to biased analysis because it is assumed that trees register perfectly all the fires in their rings (Reed *et al*. 1997). This is so because it is not feasible to confirm whether the more recently burned areas hide a previous fire (Fall 1998). Spatial fire recurrence (emerging from multiple fire scars layers overlay) is easily determined by accounting for the wildfires iterated in a geographic unit. We propose such a spatial concept to avoid the ambiguity in estimates of fire frequency present in several works.

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