

Identifying location and causality of fire ignition hotspots in a Mediterranean region

José Ramón Gonzalez-Olabarria^{A,E,F}, Lluís Brotons^{A,B}, David Gritten^{A,C}, Antoni Tudela^D and José Angel Teres^D

^ACentre Tecnològic Forestal de Catalunya (CTFC), Carretera Sant Llorenç de Morunys, E-25280 Solsona, Spain.

^BCentre for Ecological Research and Applied Forestries (CREAF), Autonomous University of Barcelona, Bellaterra, E-08193 Cerdanyola del Vallès, Spain.

^CRECOFTC – The Center for People and Forests, PO Box 1111, Kasetsart Post Office, Bangkok, 10903, Thailand.

^DServei de Prevenció d'incendis, Departament de Medi Ambient i Habitatge, Generalitat de Catalunya, E-08130 Santa Perpètua de Mogola, Spain.

^EPresent address: Carretera de Sant Llorenç de Morunys km 2, CTFC, E-25280, Solsona, Lleida, Spain.

^FCorresponding author. Email: jr.gonzalez@ctfc.es

Abstract. Fire ignitions tend to be spatially aggregated depending on their causality. In highly populated regions, such as the northern Mediterranean basin, human activities are the main cause of ignitions. The ability to locate zones with an intense and recurrent history of fire occurrence and identify their specific cause can be helpful in the implementation of measures to reduce the problem. In the present study, kernel methods, non-parametric statistical methods for estimating the spatial distribution of probabilities of point-based data, are used to define ignition hotspots based on historical records of fire ignitions in Catalonia for the period 1995–2006. Comparison of the cause of the ignitions within the area of the hotspots enabled analysis of the relation between the cause of the ignitions and the occurrence of hotspots. The results obtained highlighted that the activity of arsonists showed strong spatial clustering, with the share of intentionally caused ignitions within the hotspot areas accounting for 60.1% of the fires, whereas for the whole of Catalonia they only represented 24.3%. The findings of the study provide an opportunity to optimally allocate law-enforcement and educational resources within hotspot areas.

Additional keywords: arsonist activity, Catalonia, ignition causality, kernel analysis.

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Introduction

Fire ignition patterns are an intrinsic property of fire regimes and are therefore associated with key mechanisms in fire activity in a given region. In the case of fire regimes strongly linked to human activities, a strong spatial autocorrelation of fire ignitions may be expected owing to the autocorrelated spatial pattern of human activities in the landscape (Terradas and Piñol 1996). The identification of spatiotemporal patterns of fire occurrence at regional scales in these cases may provide valuable information for optimising the allocation of resources for forest firefighting strategies (Carmel *et al.* 2009). Such knowledge will enable the improvement of preventive firefighting strategies dealing with the initial stages of fire by focussing efforts on areas where fires are more likely to start. These strategies can be focussed on the reduction of the number of fire ignitions or on the containment of potentially large fires in

higher-risk areas, which can help the forest fire-management authorities prioritise their limited resources (Martell 2007). Actions aimed at reducing the number of ignitions can include educational campaigns or law-enforcement measures that target sensitive areas. Additionally, an adequate allocation of vigilance efforts and fire-suppression brigades can shorten the response time of those brigades to incipient fires (Genton *et al.* 2006; MIMAM 2007).

Fire ignitions have been reported to have both specific spatial (Rorig and Ferguson 1999; Podur *et al.* 2003; Genton *et al.* 2006) and temporal occurrence patterns (Prestemon and Butry 2005), matching different environmental or socioeconomic factors. For example, in the case of intentional fires, Prestemon and Butry (2005) and Genton *et al.* (2006) found that fires caused by arsonists were more spatially clustered than other types of ignitions. In Spain, for example, aggregations in space

or time can be expected for intentionally caused fires. Some of the main motivations identified in Spain as precursors for intentional fires may follow repetitive conduct patterns (MIMAM 2007). For example, compulsive behaviour can be expected in the case of some arsonists or in the case of people who light fires driven by local disputes. In these cases, defining the spatial location where uncharacteristically high ignition activity is occurring will help not only in the identification of the cause of an ignition but also provide some clues about the identity of the arsonist. Such information can be used to more effectively allocate preventive resources, or to seek those responsible for the damage if arson was the cause. Many areas within the northern Mediterranean Basin are characterised by the presence of high population densities as well as a high density of high-risk wildland–urban interfaces. These areas are characterised by intense human activity close to an important source of hazardous fuels, causing an increase in the frequency of non-natural fires, both intentional and unintentional (INDESCAT 2008). Additionally, these fires tend to occur close to urban areas, increasing the possible damage to dwellings and injuries to people (Prestemon *et al.* 2002; Badia-Perpinyà and Pallares-Barbera 2006), and occasionally disrupting the activity of fire-suppression brigades (Cohen 2008). In a context in which effective firefighting is made difficult by land-use patterns and human activities, the analysis of ignition patterns aimed at guiding early firefighting strategies becomes a priority in fire planning.

One method commonly used to visualise spatial variations in the frequency of point-based observations is kernel estimation. The flexibility and simplicity of kernel methods have been reported previously, with its use quite common in home-range studies dealing with wildlife habitat and movement (Worton 1989). During recent years, kernel methods have also been applied to convert point-based fire data into maps illustrating fire intensity (Podur *et al.* 2003; de la Riva *et al.* 2004; Koutsias *et al.* 2004; Amatulli *et al.* 2007). These studies have shown the usefulness of kernel methods if areas with a high ignition density are to be identified.

The present study aims to identify and characterise areas where an unexpectedly high density of ignition events is observed. We used, for this purpose, ignition data from Catalonia across a period of 12 years (1995–2006) and kernel methods to identify ignition hotspots from patterns in spatial distribution. Additionally, the causality of ignitions within the hotspots area was analysed to identify to which degree ignition hotspots can be linked to specific ignition causes. For this purpose, we compared variations between the overall patterns in ignition causality for Catalonia and the causality patterns of the ignitions occurring within the hotspot areas.

Material and methods

Located in the north-east of the Iberian Peninsula, the study area, Catalonia, occupies an area of over 32 000 km², mainly dominated by Mediterranean climate (Terradas and Piñol 1996). However, its diverse topography, with an elevation from sea level to over 3000 m above sea level, induces important variations in climatic conditions (temperature and precipitation regime). Such heterogeneity of conditions has led to remarkable differences in the presence of human settlements, human

activities and landscape configurations. Additionally, Catalonia is one of the most populated regions of Spain, with a population of over 7 million in 2007 (INDESCAT 2008).

The combination of dense population and forest abundance has resulted in the expansion of wildland–urban interfaces, leading to increasing exposure of humans and their property to wildfire. Like most of the regions in the northern Mediterranean basin, Catalonia is accustomed to the presence of recurrent forest fires. However, during 1994, a total of 1217 fires burned ~76 500 ha in the region, killing four people and necessitating the evacuation of thousands of people. Such disastrous events, and the resulting public concern, resulted in the understanding that it was necessary to optimise firefighting strategies. One of the identified priority action points agreed on was the improvement and development of methods for detecting and mapping fire ignitions and identifying their likely causes.

Additionally after 1994, actions were taken to improve and update a spatial database of fire ignitions. These measures included the introduction of global positioning systems (GPS) and new data recording systems, the implementation of specific courses focussing on improving personnel skills on ignition cause identification, and the refinement of cooperation protocols between the different police forces and the administration personnel working on forest fires. Such measures led to two clear improvements in the process of recording ignition events. On the one hand, the number of reported ignitions and their location accuracy increased, with the accuracy improving with the minimum burned area required to identify a fire ignition being scaled down to 0.01 ha. On the other hand, the identification of ignition cause was also improved, with a significant reduction in the number of fires of unknown origin. Both these factors are significant in achieving the aims of the current paper.

The present study analyses the ignitions that occurred during the period 1995–2006. During that period, a total of 8187 fire ignitions were reported in Catalonia, with the proportion of ignitions with an unknown cause being less than 12%.

The number of fire ignitions in Catalonia during the study period varied from a maximum of 961 in 1998 to a minimum of 448 in 2004. Regarding the ignition causes, human-related ignitions accounted for almost 80% of all the ignitions with an identified cause, with accidents and arson being the most common causes (Fig. 1).

Kernel methods

Kernel methods were used to define ignition hotspots using ignition data from the period 1995–2006 in Catalonia. Kernel analysis is a non-parametric statistical method, used in the present study for estimating the spatial distribution of ignition probabilities across Catalonia. Using a dataset of ignition points as input, the kernel analysis is able to estimate the ignition probability of any location in the study area based on the location of observed events, creating a continuous distribution of ignition probabilities.

In our case, the kernel function is a normal bivariate distribution curve (Eqn 1) based on the location of observed ignitions.

$$K(x, y) = \frac{1}{2\pi nh^2} \sum_{i=1}^n \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2h^2}\right) \quad (1)$$

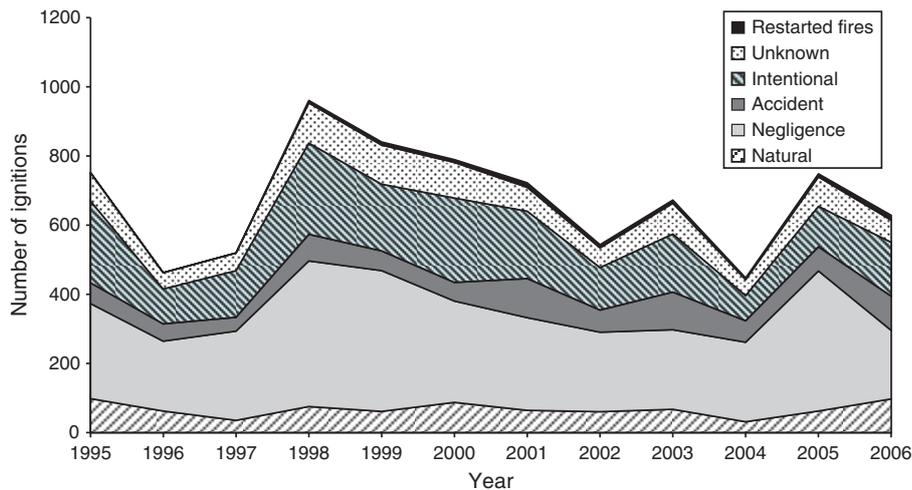


Fig. 1. Evolution of the numbers of ignitions depending on their cause, during the period 1995–2006.

where $K(x, y)$ is a density function of ignition probability estimated for a point with coordinates (x, y) , h is the smoothing factor or bandwidth that defines the level of dispersion of the density function with respect to the observed ignition points, n is the number of observed ignitions, and x_i and y_i are the coordinates of those observed ignitions. Two different methods are usually available to estimate the distribution of probabilities by kernels: fixed kernels and adaptive kernels. In the present study, we used a fixed kernel, which keeps a constant smoothing factor for any point in the study area.

One critical step in the method’s application is the selection of the smoothing factor. Kernel methods are very flexible, and choosing the smoothing factor has a determinant effect on the final outcomes (Silverman 1986; Worton 1995), as it determines the level of aggregation of the data in the density function. However, no consensus has been reached about the methodology to select the optimal smoothing factor (Silverman 1986; Brunson 1995), with the selection of the smoothing factor depending on the objectives of the study. One relatively straightforward and commonly applied method (Worton 1995) is to refer the final smoothing factor to a reference parameter (h_{ref} in Eqn 2):

$$h_{ref} = n^{-1/6} \sqrt{\frac{\text{var}_x + \text{var}_y}{2}} \quad (2)$$

where h_{ref} is the reference parameter used to define the final h , n is the number of ignitions and var_x and var_y are the estimated standardised variances of the x and y coordinates. For the study, a smoothing parameter of $0.1 \times h_{ref}$ was selected. By choosing a small smoothing parameter, it was possible to obtain sharp changes in the density of ignition probability across the study area, a desired characteristic for this analysis.

The kernel analysis was based on the HRE (Home Range Extension) package in *ArcGis v. 9.0* (ESRI Inc., Redlands, CA) developed by the Centre for Northern Forest Ecosystem Research (CNFER (Rodgers and Carr 1998)). The HRE system did not present the result as a continuous grid of probability densities, but instead generated polygons or isopleths. The

isopleths are based on percentage volume contours (PVCs). The PVC defines volumes under the utilisation distribution, and encloses areas with a defined proportion of ignitions in the smallest possible area. For example, the 0.1 and 0.9 probability isopleths represent the minimum area containing ~10 and 90% of the observed ignitions respectively (Fig. 2). Areas contained by the lowest-probability isopleths (i.e. 0.1) are the areas with the highest density of ignitions, and are at the same time contained by larger areas with higher probability of ignition occurrence but lower ignition density. In our case, only the isopleths defining areas with higher probability of ignition were used (0.1 and 0.2 probability isopleths, two darkest grey shades in Fig. 2).

Analysing the causes of ignitions in hotspots

Based on the ignitions recorded in Catalonia, regardless of the ignition cause, we identified areas with a high ignition occurrence rate (ignition hotspots), defined by the 0.1 and 0.2 probability isopleths, for each of the years of the study period 1995–2006. Once the hotspot areas had been defined for each of the years studied, we identified whether ignitions were within or outside the hotspot areas, and checked their causality (intentional, unknown, accident, natural, negligence or restarted from a previous wildfire). Based on this new information, the percentage of ignitions per cause was calculated inside the hotspot areas for each year and compared with the percentage of ignitions per cause occurring in all Catalonia during the same year. From this analysis, we determined if, during the whole study period or for a single year, there were any ignition causes that tended to be significantly more common within hotspot areas, and for how many years this tendency was observed.

Additionally, the annually delimited hotspots from all the years were overlaid, in order to generate a map indicating the recurrence of hotspots (number of years that an area was considered as a hotspot). This map was subsequently overlaid with the whole set of fire ignitions (8187 ignitions from 1995 to 2006) to identify the ignitions that were located in areas with a history of hotspot recurrence. By comparing the ignitions, their

causes and if they fell within areas with hotspot recurrence with the number of years defining the hotspot recurrence, we were able to relate the presence of recurrent hotspots to the presence of a specific cause of fire ignitions.

Results

Ignition hotspots

The distribution of the identified hotspots for the years 1995–2006 showed that in the case of hotspots defined by the 0.2

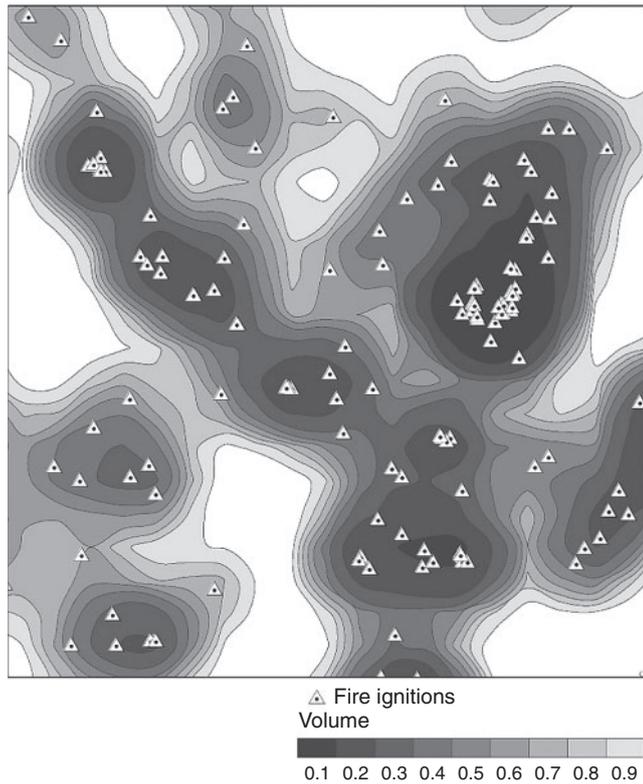


Fig. 2. Estimation of ignition probability contours using the kernel method. Each contour encloses an area with an ignition probability occurrence defined by the volume.

ignition probability, the average number of hotspots per year was 25.1, enclosing a mean surface area per hotspot of 2670 ha. For the hotspots defined by the 0.1 ignition probability, the average number of hotspots per year decreased significantly to 10.4. Their area also decreased, but not as drastically, to a mean value of 2177 ha (Table 1). Compared with the total area of Catalonia, the hotspots defined by the 0.2 ignition probability threshold occupied between 2.76% in 2005 and 1.35% in 1997 of the territory. For hotspots defined by the 0.1 ignition probability threshold, the area occupied was 1.03% in 2005 and 0.40% in 1997. Regarding their location, most of the hotspots occurred in the north-east and centre-east of Catalonia, near the Mediterranean coast (Fig. A1 of Appendix 1), where most of the urban and wildland–urban interfaces are located (Fig. A2). Additionally, it is possible to visually identify recurrence patterns at their location across the period studied.

Analysis of ignition causes within hotspots

Restarted and intentional ignitions were the only type of ignitions that tended to occur within the hotspots limits (Table 2), showing a clear tendency to be spatially aggregated in areas with high ignition densities. In the case of intentional ignitions, this spatial aggregation pattern was observed to be much higher than for any other type of ignitions, with the share of intentional ignitions being higher as the density of ignitions per area defining the hotspot increased (Fig. 3, Table 2). Of all the ignitions occurring in Catalonia during the period 1995–2006, 24.3% were intentional. Further, these types of ignitions represent 48.6% of all the ignitions occurring within the limits of the $P=0.2$ hotspots, reaching 60.1% inside the $P=0.1$ hotspots. Such tendency of intentional ignitions to be grouped in hotspots was detected for all the years analysed (Table 3). Those fires that had natural causes or were caused by accidents or negligence usually started outside the area delimited by the hotspots.

Analysing the effect of hotspot recurrence

When the effect of hotspots recurrence on ignition causality was analysed, our results showed that locations with a history of repeated high density of ignitions were usually associated with

Table 1. Summary of hotspots identified by kernel analysis ($P=0.2$ or 0.1) per year as represented in Fig. A1

Year	$P=0.2$				$P=0.1$			
	<i>n</i>	Total area (ha)	Mean area (ha)	s.d.	<i>n</i>	Total area (ha)	Mean area (ha)	s.d.
1995	14	49 955	3568	3199	6	16 471	2745	2031
1996	16	56 248	3516	3333	6	16 602	2767	2514
1997	12	43 374	3614	2312	6	12 872	2145	1291
1998	28	60 394	2157	2468	9	17 736	1971	2002
1999	34	68 063	2002	2694	13	24 573	1890	2573
2000	29	78 120	2694	3149	18	25 853	1436	1347
2001	24	54 827	2284	2463	10	18 688	1869	2001
2002	34	78 576	2311	3523	13	30 726	2364	2215
2003	17	46 761	2751	5365	8	16 022	2003	2065
2004	28	74 660	2666	3606	11	25 910	2355	1553
2005	38	88 479	2328	4940	18	32 993	1833	2259
2006	27	58 051	2150	3274	7	19 251	2750	1179

Table 2. Analysis of grouping tendencies per cause for the whole period 1995–2006

χ^2 is the value of Pearson's Chi-square if the frequency of ignitions in the whole of Catalonia are compared with the frequency of ignitions in the hotspots ($P = 0.2$ or 0.1). The Tendency column indicates, for those causes that show significant differences in their level of grouping ($P < 0.05$), if the ignitions tend to aggregate in hotspots (+) or avoid them (-)

Cause	$P = 0.2$			$P = 0.1$		
	χ^2	P	Tendency	χ^2	P	Tendency
Intentional	479.77	<0.001	+	605.80	<0.001	+
Unknown	0.30	0.585		0.08	0.777	
Accident	18.27	<0.001	-	1356.58	<0.001	-
Natural	123.76	<0.001	-	112.81	<0.001	-
Negligence	162.31	<0.001	-	795.58	<0.001	-
Restart	11.72	<0.001	+	12.32	<0.001	+

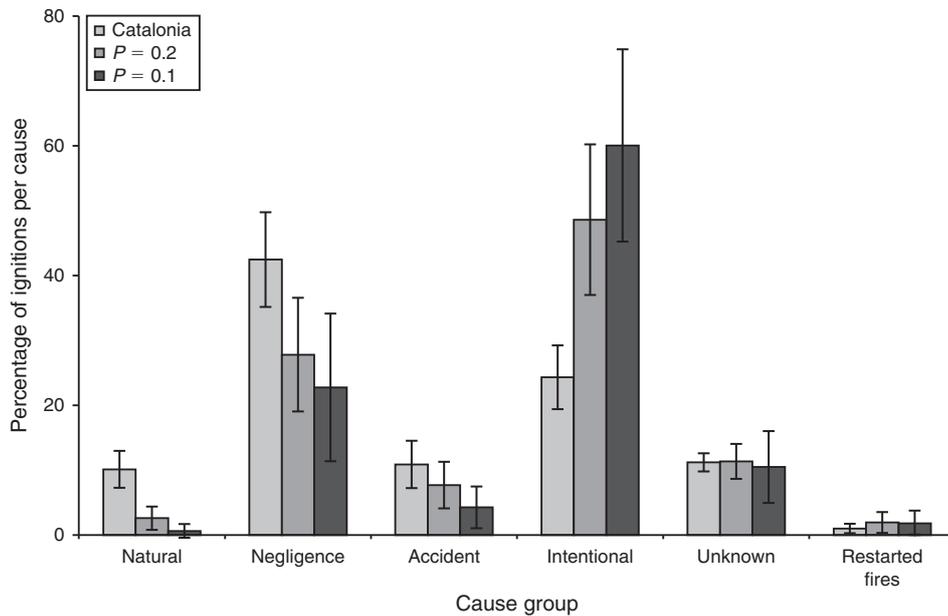


Fig. 3. Mean and standard deviation of the annual percentage of ignitions per group of causality and location (all Catalonia; within $P = 0.2$; or within $P = 0.1$ hotspots).

Table 3. Analysis of grouping tendencies during the period 1995–2006

Each column indicates the number of years with a significant tendency ($P < 0.05$) of ignitions to occur inside the area of the hotspots (+), outside the area of the hotspots (-), or with no significant relation between ignitions and hotspot allocation

Cause	Number of years that the ignitions tend to occur inside (+) or outside (-) hotspots					
	$P = 0.2$			$P = 0.1$		
	(+)	(-)	No difference	(+)	(-)	No difference
Intentional	12	0	0	12	0	0
Restart	2	0	10	0	0	12
Accident	0	3	9	0	12	0
Natural	0	11	1	0	12	0
Negligence	0	8	4	0	12	0
Unknown	0	0	12	0	0	12

fires that were started intentionally. By overlaying the annual hotspot areas, we found that hotspot areas were a common feature over time, and were associated with the presence of intentional ignitions (Fig. 4). Additionally, a steady rise in the

relative importance of intentional ignitions was observed parallel to the increase in the recurrence of hotspots (Fig. 4), with the percentage of intentional ignitions being 43.7% in areas where hotspots were identified during 2 years, and reaching a

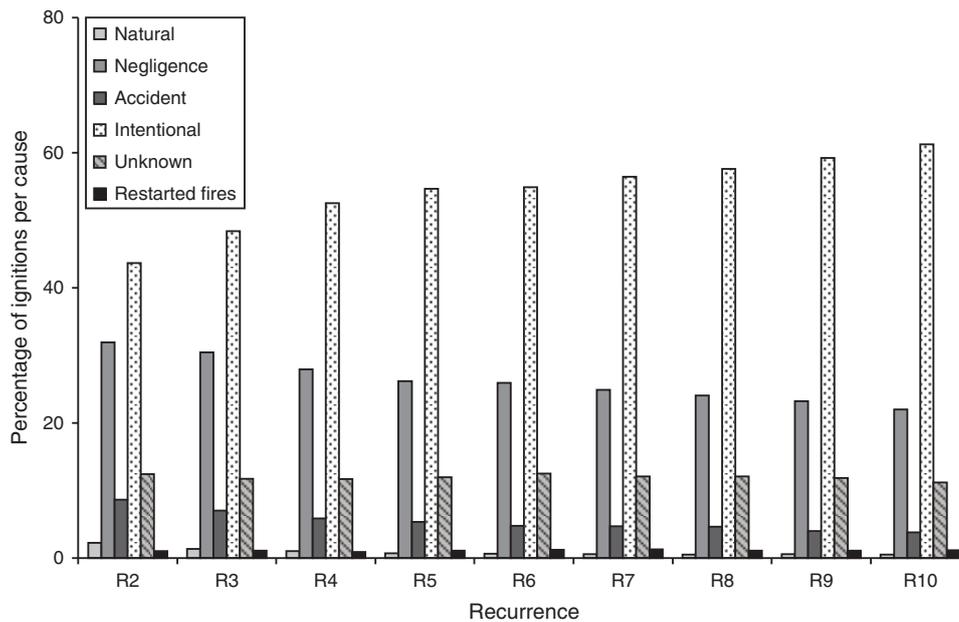


Fig. 4. Effect of hotspot recurrence on ignition causality. The number of years that an area is identified as a $P=0.2$ hotspot is defined by R2 if it is a hotspot during 2 years, R3 if it is a hotspot during 3 years and so on.

value of 61.2% in locations where hotspots were identified in 10 of the 12 study years.

Discussion

In the present study, we analysed the causes of fires leading to ignition hotspots. Our results showed that intentionally caused fires tended to be spatially grouped in areas where a higher ignition activity was reported. This is in line with the findings of Genton *et al.* (2006) that criminally intentional fires tend to be clustered. This, according to Prestemon and Butry (2005), is partially explained by the finding that a successful arson attempt is an encouragement to light more fires. This grouping tendency was identified for each of the years of the study period. Additionally, those areas with a history of reoccurrence of ignition hotspots also had an even higher presence of intentional fires. The criminal nature of intentional fires, and their importance in the region in terms of relative number, underlines the importance of the findings. This is supported by the fact that wildland fires that are acts of arson are mostly close to economically valuable structures (Butry *et al.* 2002; Omi 2005), highlighting the need for further development of tools for fire prevention. For example, increasing the knowledge available for forest fire management agencies, including providing spatiotemporal clustering, as has been carried out in the present work, would greatly assist them to do their jobs (Prestemon and Butry 2005; Genton *et al.* 2006).

Tackling the problem of intentional fires requires specific preventive strategies, ranging from a visible increase in the number of law-enforcement agents in high-risk locations to deter criminal activities, to the prosecution of arsonists. These preventive measures require the reallocation of crime-fighting resources for this specific task. However, this could come at a cost of hindering other crime-fighting activities (Prestemon and

Butry 2005). The possibility of defining a potential area of activity of an arsonist using previous statistics on ignition location can ease the work of those agencies responsible for reducing the number of fires, including law-enforcement agencies. For example, Martell (2007) points out that forest fire management agencies have numerous responsibilities, including mitigating the damage that results from wildfires. They must do this with minimal costs; therefore, they must utilise their resources as efficiently as possible, for example, in determining the location of fire-response bases; rapid response is a key factor in minimising fire size. Allocating fire-prevention and vigilance efforts to areas of ignition hotspots not only enables the improvement of fire detection, and therefore the effective time response of fire brigades, but also targets illegal activities that tend to lead to the appearance of an ignition hotspot. Additionally, the presence of high densities of fires and the activity of an arsonist spatially correlated and recurrent in time makes it possible to generate a hypothesis about the cause of new fires in certain locations.

The present study dealt only with the causes of fire ignition that led to ignition hotspots, but the strength of its results calls for a deeper understanding of the patterns of intentionally caused fires. For example, a refinement of the study including analysis at an individual hotspot-level may provide additional information about differences in the behaviour patterns between arsonists. The results of the present study, and a comparison between hotspot allocations versus well-documented records on arsonist activities (mainly based on police reports) encouraged the Catalanian government to use this approach in real fire prevention. An early alert system has been developed by the fire-prevention services to pre-empt potential activity of arsonists. This system compares, every 15 days, the hotspots produced with the ignition data recorded during the previous 12 months against the allocation of historic hotspots (Fig. A1). This

comparison allows the identification of incipient hotspots, also providing a probable cause for new ignitions within consolidated hotspot areas (areas where the incipient hotspots spatially match historic hotspots).

We have shown that fire ignition causes in the region of Catalonia are not randomly distributed in space, and that the identification of ignition hotspots where most ignitions occur provides useful information on the spatial location of ignitions most likely to be affected by firefighting and police actions. In this context, we suggest that the implementation of ignition mapping and hotspot identification protocols may be a cornerstone of a more effective fire policy in regions where non-natural causes are behind most wildfires. Our approach could therefore be extended and be of great potential value, not only to other regions of Spain, but also to the rest of the Mediterranean region, with a current percentage of human-caused ignitions leading to forest fires of ~90% (FAO 2007). There is, however, still room for further research that can enhance and complement the results of this study, such as individually analysing the spatial and temporal patterns of ignition hotspots occurrence for each ignition cause. By segregating the data on ignitions before analysing the occurrence of ignition hotspots, it would be possible to better identify the factors underlying the aggregation patterns of the fire ignitions (Badia *et al.* 2002; González-Olabarria *et al.* 2011).

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References

- Amatulli G, Perez-Cabello F, de la Riva J (2007) Mapping lightning/human-caused wildfires occurrence under ignition-point location uncertainty. *Ecological Modelling* **200**, 321–333. doi:10.1016/J.ECOLMO DEL.2006.08.001
- Badia A, Saur D, Cerdan R, Llordes JC (2002) Causality and management of forest fires in Mediterranean environments: an example from Catalonia. *Environmental Hazards* **4**(1), 23–32. doi:10.3763/EHAZ.2002.0403
- Badia-Perpinyà A, Pallares-Barbera M (2006) Spatial distribution of ignitions in Mediterranean periurban and rural areas: the case of Catalonia. *International Journal of Wildland Fire* **15**, 187–196. doi:10.1071/WF04008
- Brunsdon CF (1995) Estimating probability surfaces for geographical point data: an adaptive kernel algorithm. *Computers & Geosciences* **21**, 877–894. doi:10.1016/0098-3004(95)00020-9
- Butry DT, Pye JM, Prestemon JP (2002) Prescribed fire in the interface: separating the people from the trees. In 'Proceedings of the Eleventh Biennial Southern Silvicultural Research Conference'. (Ed. KW Outcalt). USDA Forest Service, Southern Research Station, General Technical Report GTR-SRS-48, pp. 132–136. (Asheville, NC)
- Carmel YS, Pazb S, Jahashana F, Shoshanya M (2009) Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management* **257**(1), 370–377. doi:10.1016/J.FORECO.2008.09.039
- Cohen J (2008) The wildland–urban interface fire problem forest history today: a consequence of the fire exclusion paradigm. *Forest History Today* (Fall), 20–26. Available at http://www.fs.fed.us/rm/pubs_other/rmrs_2008_cohen_j002.pdf [Verified 12 June 2012]
- de la Riva J, Pérez-Cabello F, Lana-Renault N, Koutsias N (2004) Mapping wildfire occurrence at regional scale. *Remote Sensing of Environment* **92**, 288–294. doi:10.1016/J.RSE.2004.06.013
- FAO (2007) Fire Management Global Assessment 2006. Food and Agriculture Organization of the United Nations, FAO Forestry Paper Number 151. A thematic study prepared in the framework of the Global Forest Resource Assessment 2005. (Rome)
- Genton MG, Butry DT, Gumpertz ML, Prestemon J (2006) Spatiotemporal analysis of wildland fire ignitions in the St Johns River Water Management District, Florida. *International Journal of Wildland Fire* **15**, 87–97. doi:10.1071/WF04034
- González-Olabarria JR, Mola-Yudego B, Pukkala T, Palahí M (2011) Using multiscale spatial analysis to assess fire ignition density in Catalonia, Spain. *Annals of Forest Science* **68**, 861–871. doi:10.1007/S13595-011-0082-2
- INDESCAT (2008) 'Anuari Estadístic de Catalunya.' (Institut d'Estadística de Catalunya: Generalitat de Catalunya) Available at <http://www.idescat.cat/pub/?id=aec> [Verified 12 June 2012]
- Koutsias N, Kalaboukis KD, Allgöwer B (2004) Fire occurrence patterns at landscape level: beyond positional accuracy of ignition points with kernel density estimation methods. *Natural Resource Modeling* **17**(4), 359–375. doi:10.1111/J.1939-7445.2004.TB00141.X
- Martell DL (2007) Forest fire management: current practices and new challenges for operational researchers. In 'Handbook of Operations Research in Natural Resources'. (Eds A Weintraub, CR Trond Bjørndal, R Epstein, J Miranda) (Springer Science+Business Media Publishing: New York)
- MIMAM (2007) 'Los Incendios Forestales en España Año 2007.' (Ministerio de Medio Ambiente y Medio Rural y Marino: Madrid)
- Omi PN (2005) 'Forest Fires: a Reference Handbook.' (ABC-CLIO: Santa Barbara, CA)
- Podur J, Martell DL, Csillag F (2003) Spatial patterns of lightning-caused forest fires in Ontario, 1976–1998. *Ecological Modelling* **164**, 1–20. doi:10.1016/S0304-3800(02)00386-1
- Prestemon JP, Butry DB (2005) Time to burn: modeling wildland arson as an autoregressive crime function. *American Journal of Agricultural Economics* **87**(3), 756–770. doi:10.1111/J.1467-8276.2005.00760.X
- Prestemon JP, Pye JM, Butry DT, Holmes TP, Mercer DE (2002) Understanding broad-scale wildfire risks in a human-dominated landscape. *Forest Science* **48**, 685–693.
- Rodgers AR, Carr AP (1998) HRE: the Home Range Extension for ArcView. Ontario Ministry of Natural Resources, Centre for Northern Forest Ecosystem Research. (Thunder Bay, ON) Available at <http://flash.lakeheadu.ca/~arodgers/hre/SRN-HRT.pdf> [Verified 18 March 2011]
- Rorig ML, Ferguson SA (1999) Characteristics of lightning and wildland fire ignition in the Pacific Northwest. *Journal of Applied Meteorology* **38**, 1565–1575. doi:10.1175/1520-0450(1999)038<1565:COLAWF>2.0.CO;2
- Silverman BW (1986) 'Density Estimation for Statistics and Data Analysis.' (Chapman and Hall Publishing: London)
- Terradas J, Piñol J (1996) Els grans incendis: condicions meteorològiques i de vegetació per al seu desenvolupament. In 'Ecologia del Foc'. (Ed. J Terradas) (Proa Publishing: Barcelona)
- Worton BJ (1989) Kernel methods for estimating the utilization distribution in home-range studies. *Ecology* **70**, 164–168. doi:10.2307/1938423
- Worton BJ (1995) A convex hull-based estimator of home-range size. *Biometrics* **51**, 1206–1215. doi:10.2307/2533254

Appendix 1

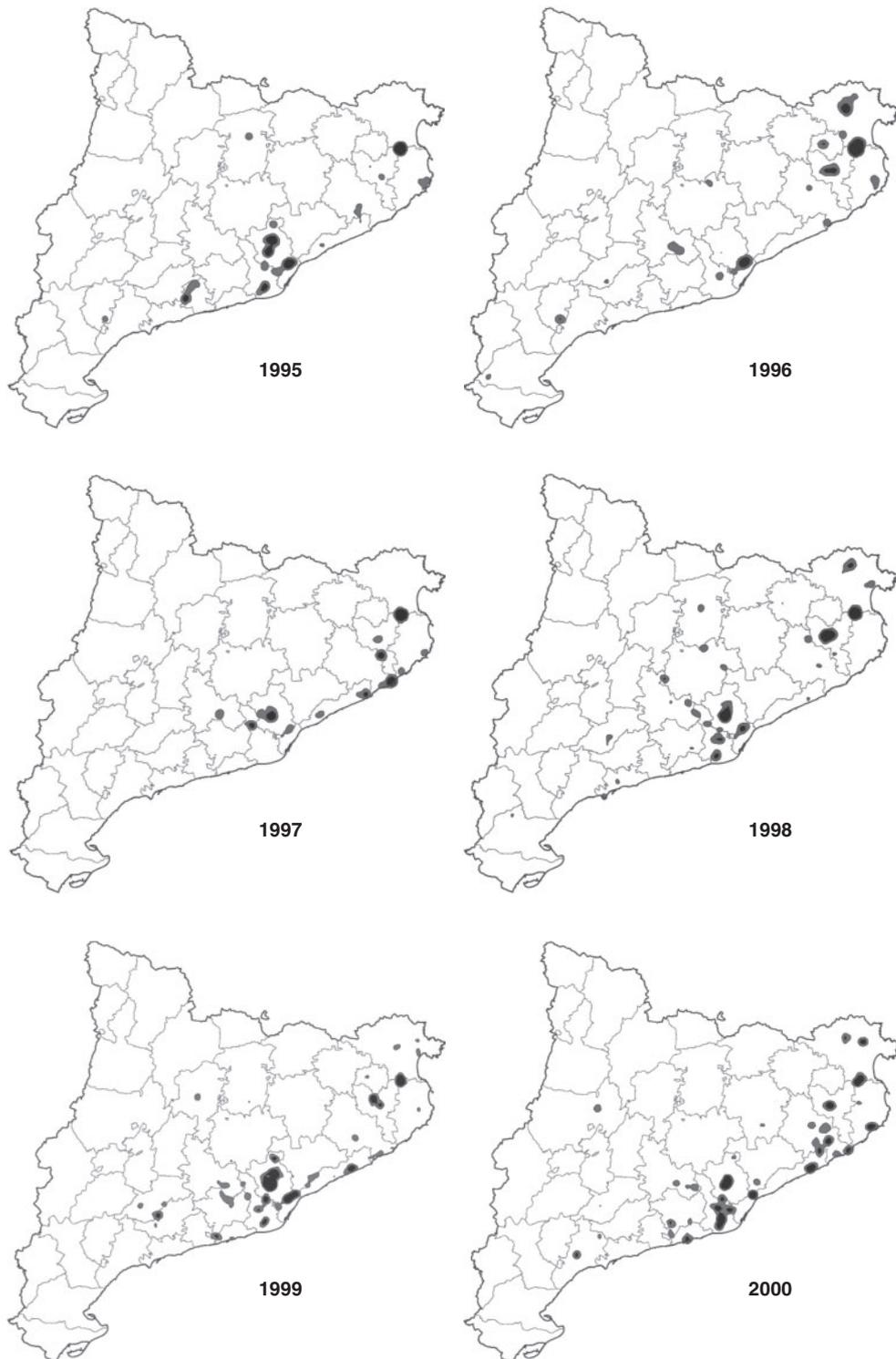


Fig. A1. Annual location of ignition hotspots.

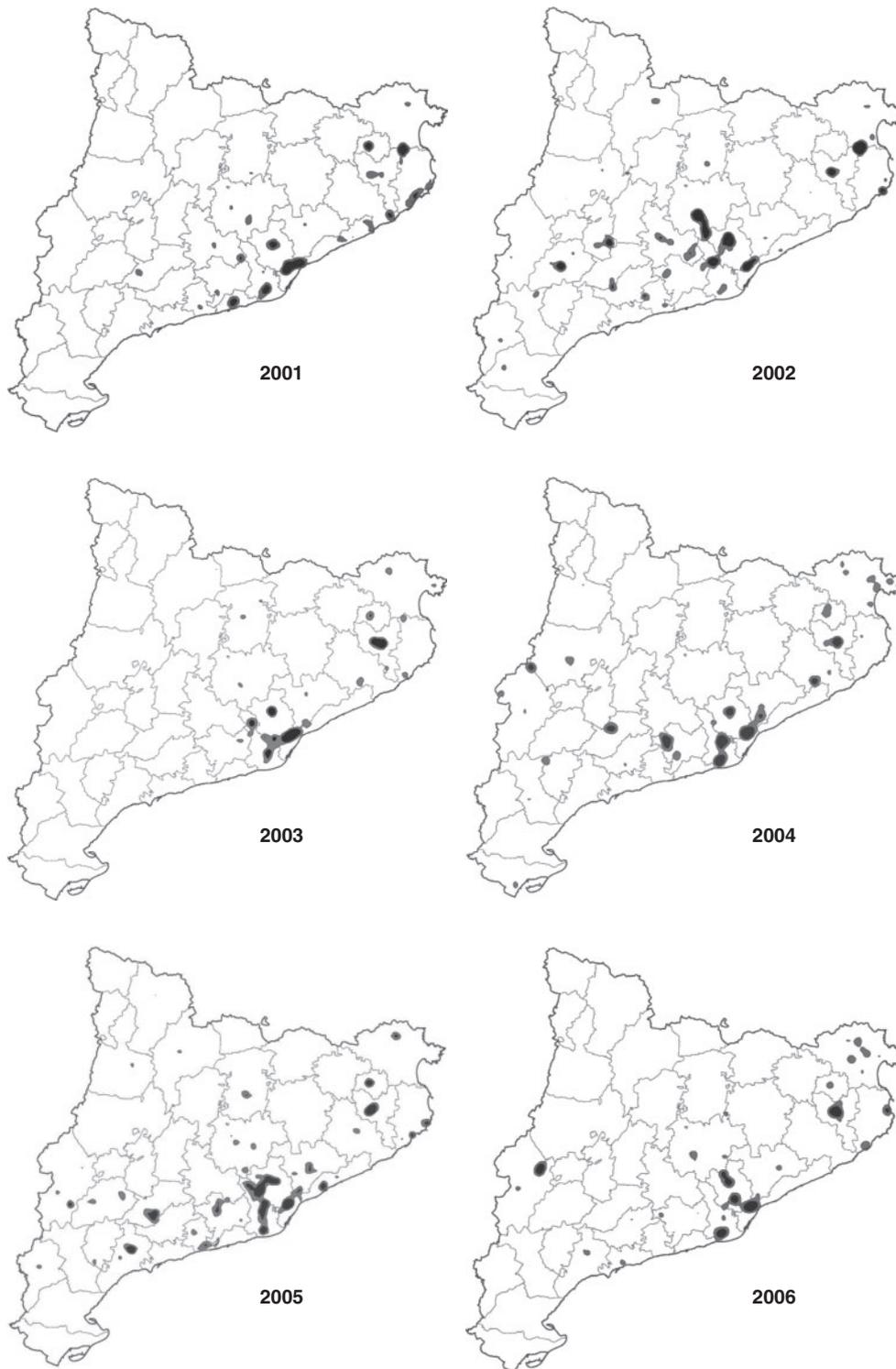


Fig. A1. (Continued)

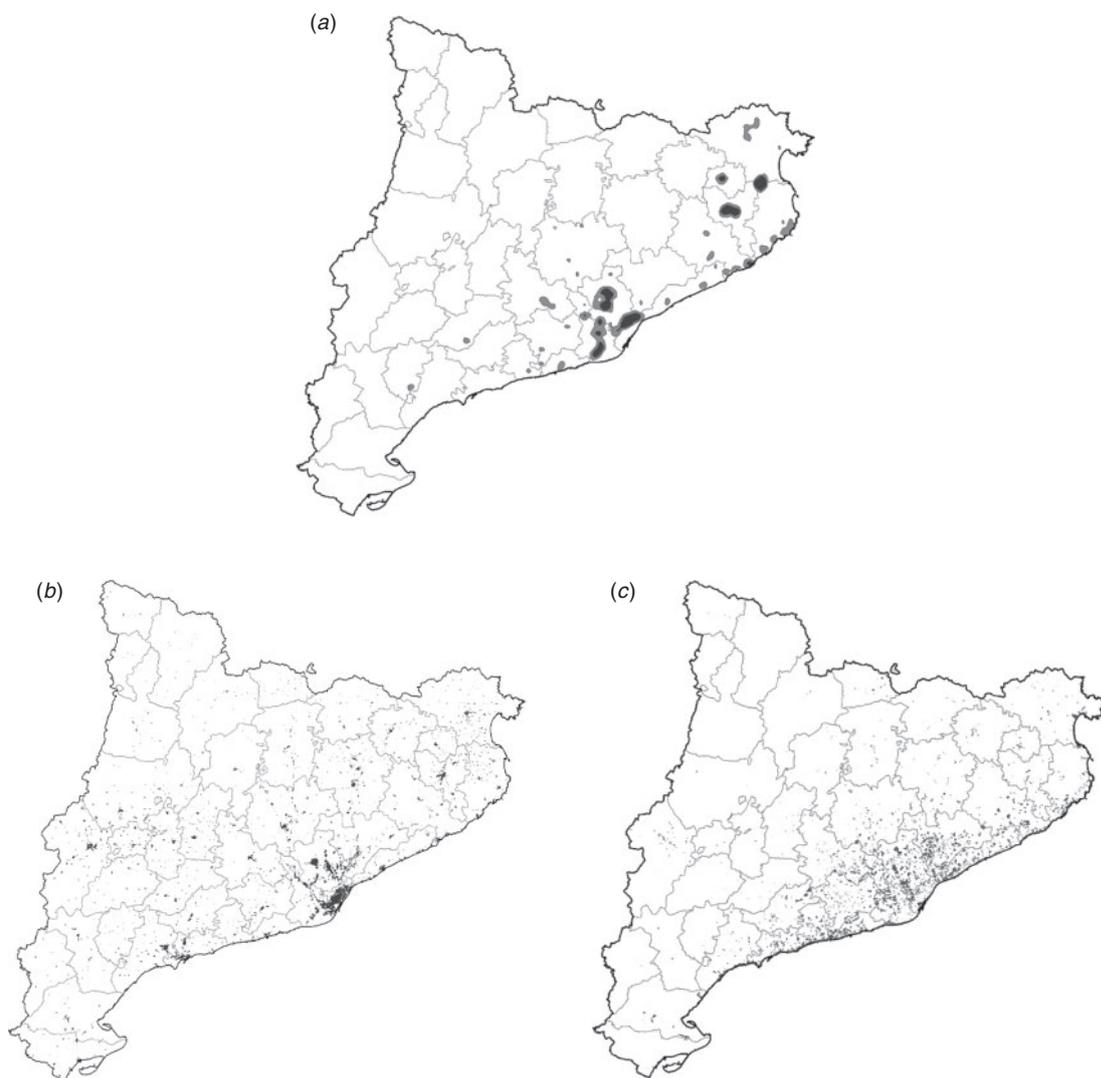


Fig. A2. (a) Hotspots in Catalonia due to the ignitions that occurred in the period 1995–2006. Dark areas have 0.1% probability of ignition; if added to the grey areas, they represent a 0.2% probability of ignition occurrence. (b) Location of the urban areas of Catalonia. (c) Location of the wildland–urban interfaces in Catalonia.