FIREfficient

Operational tools for improving efficiency in wildfire risk reduction in EU landscapes

This project is co-funded by the European Union

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Protocol for ignition risk assessment

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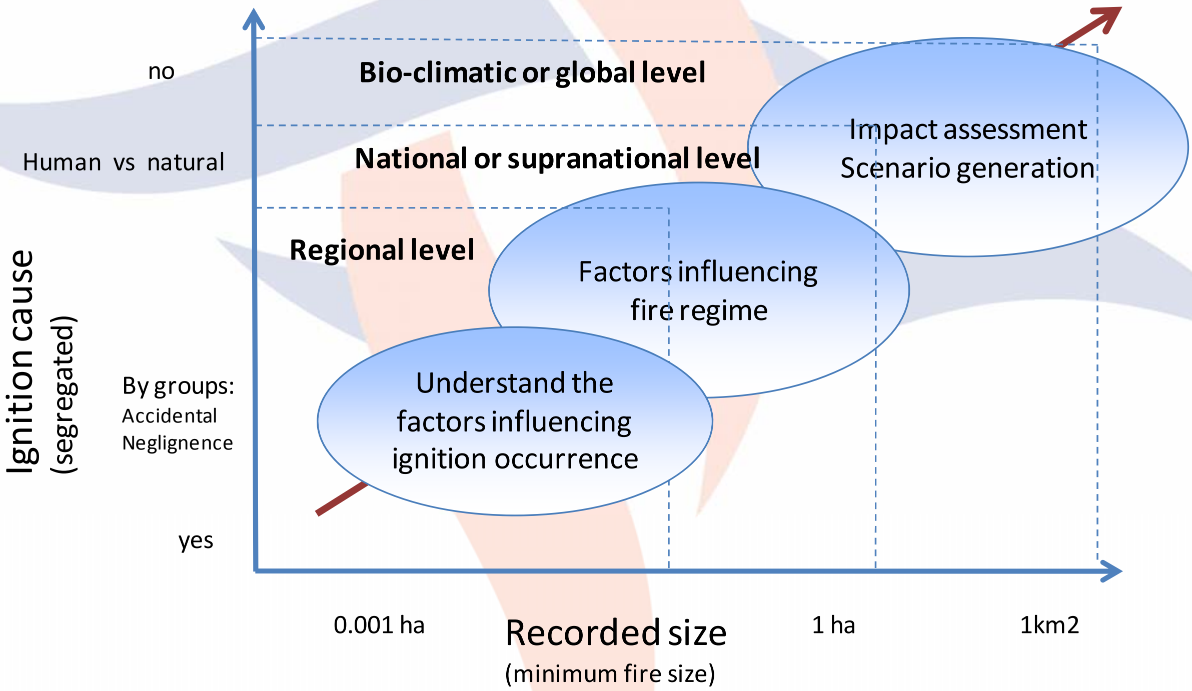
Solsona, May 2015

The occurrence of wildfires requires from the presence a heat source and specific fuel conditions to trigger an ignition or starting point were a heat source will enable the combustion of nearby fuel and the subsequent spread of the fire. Although a limited number of ignitions evolve into fires of significant size, the knowledge about their spatial and temporal distribution provides information for assessing potential risk of fire that can be used to allocate resources for early attack fires on the more risky areas (Carmel et al., 2009). For example, when combined with Fire Danger Rating Systems (FDRS) the results of models for predicting ignition occurrence with FDRS predictions we would include those socio-economic factors behind human-caused ignitions to the weather and fuel moisture components that basically define FDRS. The number and spatial distribution of ignitions can also be integrated into fire spread models to generate spatially continuous information on probability of fire occurrence for landscape planning purposes when reducing the negative impact of fires is a goal (Gonzalez-Olabarria and Pukkala 2011; Gonzalez-Olabarria et al., 2012a). Finally, by understanding the human behaviour that triggers human-caused ignitions, it is possible to implement measures for reducing the number of ignitions and the subsequent fires. However, it has to be mentioned that predicting where and when they will the ignitions take place implies a high degree of uncertainty, as both natural events and human activities leading to their occurrence are often difficult to predict or even to measure.

Adding to the inherent degree of uncertainty associated to ignition occurrence, there are several other aspects that may difficult the process of analyzing ignition occurrence, and interpret the obtained results. First, it must be realized the so called ignitions are in fact fires, as the process of recording them is associated to a minimum fire size, which depends on the requirements of regional or national administrations. Despite the known fact that only a few ignitions evolve into large fires, neglecting those "non-important" fires may be a loss of important pieces for completing the fire regime puzzle. Even if any forest fire, regardless its size requires certain fuel and moisture conditions to start, its final size depends on those factors limiting its spread (Keane et al., 2010). This implies that as the size of recorded fires increase, their distribution highly depends on factors such as: amount, type, and spatial arrangement of fuel types; previous and prevailing weather conditions; topography; and in some cases the difficulty to implement an early detection and suppression due to the remoteness of the fire initiation point. Meaning that on a study based on "important" fires, the distribution of ignitions and the source of heat causing the emergence of those fires (e.g. human activities or lighting strikes) is partially neglected. This aspect is of great importance if our objective is to identify those socio-economic factors behind the occurrence of human caused fire ignitions, as it is assumed that this knowledge can be used to define prevention measures for reducing the number of ignitions, and subsequently of fires.

Identifying the influence of socio-economic factors by modeling requires from taking decisions that may vary the potential results. For example, the choice of the statistical method and the spatial scale at which the data is aggregated should have an impact not only on the results but especially on their interpretation. This influence on the potential results becomes obvious when selecting the spatial scale to aggregate ignition data (e.g. based on the specific ignition locations as in Romero-Calcerrada et al. 2008; on the location of ignitions versus a set of random non-ignited points as in Martell et al. 1987; on an spatially continuous grid were the occurrence or the frequency of ignitions is accounted as in Cardille et al. 2001; on administrative or ecological borders as in De la Riva et al., 2004 or Chou et al., 1993; or on the combination of multiple scales as in Gonzalez-Olabarria et al., 2011), as the selected aggregation scale will define the type and availability of variables to be used as ignition precursors. Finally, another important aspect that should be taken into consideration when modelling the occurrence of ignitions of human origin is that these ignitions can hardly be considered as a uniform group as their etiology can be quite different. Traditionally, modelling the occurrence of ignitions has relied on broad causality groups, as for example natural versus human caused ignitions, or on the segregation of human cases into pooled groups (e.g. intentional, accident, negligence, restarted...). Nevertheless, it is known that causal groups as negligences or accidents are the result of merging ignitions from more specific causes such as pasture burning or other escaped agricultural burning, forest works, smokers, electric lines, railroads, campfires etc..., each one of them deriving from specific human behaviour and related activities. Subsequently the spatio-temporal aggregation of the ignitions is expected to vary depending the specific ignition cause (Prestemon and Butry 2005; Gonzalez-Olabarria et al., 2012b), and those socio-economic and environmental factors behind their occurrence will vary accordingly (Gonzalez-Olabarria et al., 2015). Therefore, by combining ignitions from pooled causes we will obtain results that depend on the ignitions that came from the more frequent cause or are more aggregated spatially, diluting the influence of the not so common ignition causes, limiting the possibility of discern accurate relations between the occurrence of ignitions and human behaviour, and hampering future studies about the influence that the cause of ignitions may have on defining the fire characteristics other than temporal and spatial distribution (Syphard and Keeley 2015).

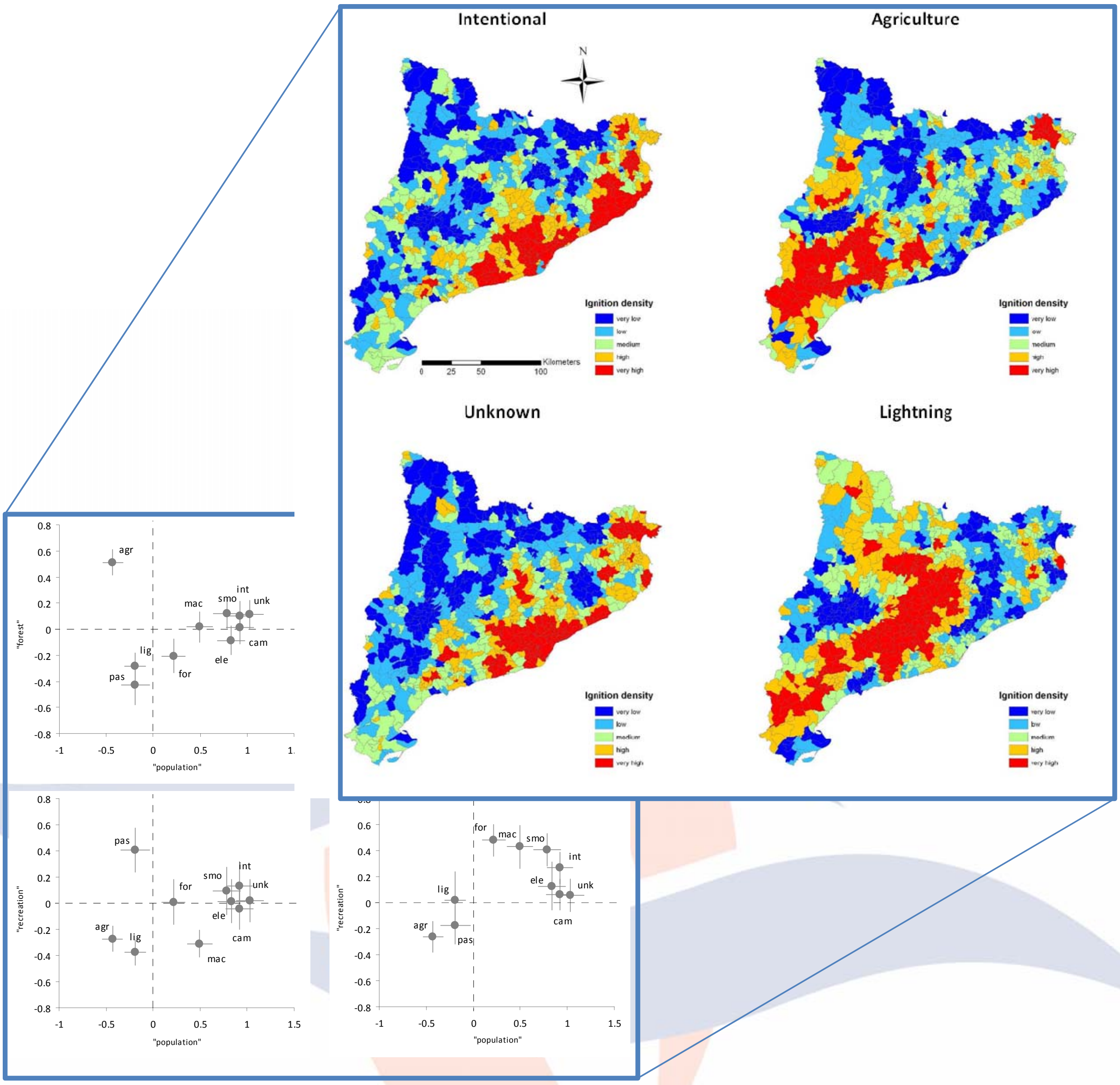


The nature of the data used for modelling predefines the utility/objective of the model

Nevertheless, it can not be said that a minimum size of the fires, or the segregation of those fires by their specific casuistic, or a specific spatial aggregation of the fires, defines the optimal choice to asses the fire ignition regime. As in any type of modelling, what makes a good model is its adequateness for answering the questions that is suppose to give a response to. In other words, if an ignition assessment model is expected to provide information about the specific factors influencing the occurrence or frequency of fires, regardless their size, we have should aim to use as modelling data all the recorded fires, and the minimum the size of the fires, the better. Additionally, as previously mentioned (Gauteaume et al., 2013; Gonzalez-Olabarria et al., 2015) differentiate the specific fire casuistic when modelling improves greatly the soundness of the results.

It has to be mentioned that this type of modelling aiming for identifying the factors behind the occurrence of fire have an important regional component, as both the fire regime, the casuistic distribution, and human behaviour varies across regions in Europe. Developing Pan-EU models on factors influencing fire ignitions does not only have the risk of combining different fire regimes and human behaviour, but also requires from an harmonization of both the ignition data and about the influencing factors surrogates, that even if possible produces a great reduction of the data accuracy as the most logic harmonization process will be to standardize to the "weakest link of the chain" or less accurate data. This reduction of the accuracy of the data can be partially solved in the case of the surrogates explaining the influencing factors, as the climatic data can be obtained at EU level, and census statistical data can be found at Nuts2 and Nuts3 from the Eurostat (http://ec.europa.eu/eurostat). In the case of the ignition data the solutions seems far more complicate, as the effort on fire recording varies across EU, mostly depending on the historic importance of fire across Countries. A partial solution may come from the methodology explained by de la Riva et al. (2004), who harmonized the ignition data at administrative level, generating danger ratings, taking into account the variability on fire frequency by using kernel distributions that are generated using various radiuses of search or bandwidths (Additional A). This methodology, reduces inaccuracy problems due to the allocation of ignitions, and also accounts for the possibility that an administrative limit is not an impermeable borders, and the activities of nearby counties or municipalities are both influencing and being influenced by the fire occurrence. Although these methods should help to partially solve the issues of the data recording variability, an analysis of the factors influencing the occurrence of forest fires should aim to identify specificities in terms of allocation of hazardous activities, if efficient prevention measures are to be planned and implemented for reducing the number of fires.

Therefore, region specific analysis are to be the basis of this type/objective oriented assessments, and an open review of regional assessments, based on a profound understanding of the reviewed studies, is expected to provide relevant information about similarities and variations across EU. On the opposite side will be an attempt to generate a Pan-EU assessment on ignitions and their subjacent causes, that will produce little and not really consistent information about the factors influencing the most common causes, on the most fire prone sites, or on regions with an history and knowledge on recording fires. This aspect being further enhanced by the tendency of EU recorded data of not splitting the information of fires caused by accidents and negligence on more specific casuistic, when it has being demonstrated that those ignitions grouped on accidental and negligence, are indeed triggered by specific causes with very different factors and follow different spatial aggregation patterns (Gonzalez-Olabarria et al., 2015)



Example of fire ignition danger rating (From Gonzalez-Olabarria et al., 2015) for the Catalonian region, using the methodology proposed by de la Riva et al., (2004), all ignition groups are given similar importance regardless the number of recorded fires. This smoothed and harmonised approach for mapping the risk of fire across a region not only gives enough importance to less common causes, but accounts for the influence of neighbouring municipalities. These characteristics of the modelling approach were found highly desirable for identifying the influence of human activities on the occurrence of fires.

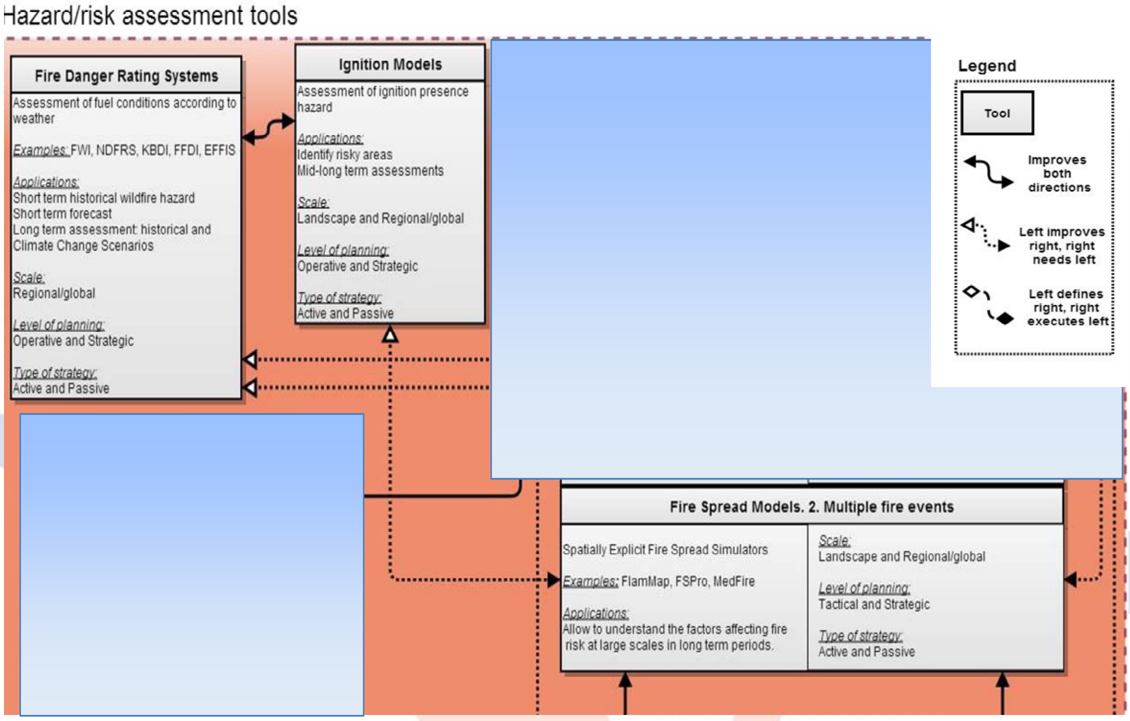
All the previously mentioned limitations are focussed on fire ignition assessment and its relation with those factors influencing their occurrence. But the utility of ignition modelling goes far beyond identifying hazardous activities triggering ignitions. Using “not so small fires (>0.1 ha)”, and not segregated by their causes, to identify the spatial and temporal variability of fire occurrence has also its relevance. This type of analysis, as said, limits the acquisition of information about the ignition casuistic and influencing factors, being limited its potential use for planning preventive measures to cut the number of fires. However, the impact of fires does not depend on their cause but on their size, intensity and the elements (human, natural, infrastructures) that they endanger. Therefore, knowing were fires are more prone to occur, when, and their expected size is a crucial piece of the risk assessment puzzle.

Although a limited number of ignitions evolve into fires of significant size, the knowledge about their spatial and temporal distribution provides information for assessing potential risk of fire that can be used to allocate resources for early attack fires on the more risky areas (Carmel et al., 2009). For example, it is possible to combine the spatial-temporal distribution of fires with Fire Danger Rating Systems, (FDRS) to validate the results from the FDRSs (Feltman et al., 2012), to use the outputs of different FDRSs as explanatory variables when modelling fire occurrence (Vega-Garcia et al., 1999; Wotton et al., 2003), or to improve danger ratings by adding the contribution of socio-economic variables related to the occurrence of fires to the fire danger indexes generated by FDRSs, which are basically based on weather related variables. FDRSs predict the potential fire behaviour of fires in terms of potential fire intensity and danger in relation to the required suppression capability, but do not include explicitly the fire spread of fires across a landscape, and their main use is to generate daily danger maps to set alerts and mobilize extinction resources across a region or country. Among the FDRSs, the Canadian fire weather index is the most commonly used, and the one available at EU level through the EFFIS system.

Another important use of the spatial and temporal distribution of ignitions is the simulation of fires for evaluating the potential fire occurrence. This assessment is implemented y including a shape-file of fire ignitions on fire spread models. The most known applications of fire spread models for prevention planning, that include the possibility of including multiple fire ignitions for evaluating fire occurrence, developed by the Missoula Fire Sciences Laboratory and the USDA Rocky Mountain Research Station, USA, (FSPro/Fire Spread Probability, and FlamMap/fire mapping and analysis system).

The FSPro is a system that calculates the probability of a fire reaches any point in a studied landscape, given an existing fire ignition or fire perimeter (Andrews 2007). It uses similar landscape information as FARSITE, but multiple different weather scenarios, FSPro performs hundreds or thousands of separate fire growth simulations using a minimum travel time fire spread method. The amount of time a fire reaches each point, combined with the total number of fire simulations, will show a fire probability surface. The FlamMap is a fire mapping and analysis system which estimate potential fire behavior across a landscape. By introducing similar landscape information in the case of FARSITE (raster maps of slope, elevation, aspect, fuel type, tree height, canopy base height, canopy bulk density, canopy cover), but constant values on fuel moisture and weather, the system produces fire behaviour calculations such as spread rate, flame length, fire line intensity, fire crowning, for each point on the studied area (Finney 2006; Stratton 2004). FlamMap also includes the ability to calculate minimum travel times for fire spread, and fire occurrence probability, which is useful in determining effective fuel treatment locations. A difference between these systems is that FlamMap is mainly designed for tactical planning of fuel management operations, whereas FSPro aims for larger surfaces and a more strategic planning frame, and considers a temporal evolution that FlamMap lacks.

Other systems including multiple fires for evaluating the potential impact of fire in the long-run are the so called vegetation succession models with main objective of simulating the dynamics of vegetation at different spatial scales. Examples of this type of models that fire is the main driver are he Lund-Potsdam-Jena Dynamic Global Vegetation Model (LPJ-DGVM), and the forest landscape models LANDIS II and LANDCLIM. However, it has to be mentioned that the main purpose of those models is academic or define very long-term strategic prevention measures.



Potential linkage between fire ignition models and other tools for assessing the risk of fire

Those ignitions can be included a random allocation of points or through a predefined shape of points where the ignitions are expected to occur during a period of time. The simpler way to include predefined fires is used the recorded ignitions as they occurred. However, if the fire regime is expected to change or if the area to be analyzed has not a good record of fires, ignition probability models are required to generate the desired ignitions, based on sound assumptions. There are several statistical methods for adjusting a fire ignition model, but most rely on the expected influence of human, vegetation or meteorological factors. In this case the need to understand the impact of those factors has a lesser importance than models developed for this sole objective, and splitting the ignition data according to causes is not so relevant. The most common methodology is the use of binary logistic regression methods due to their flexibility. Kernel methods also generate a continuous estimation of the accumulated density, based on probability density functions, and in this case they do not require influencing factors. This accumulated density can be easily transformed on a probability map that can reshape a number of random points, on a map of ignitions that differs from historic fires but still follows the similar spatial distributions. This kernel methods are quite flexible, and the resulting density functions highly depend on the selection of the smoothing factor or bandwidth (Additional B1). For example large bandwidths result on smoothed distributions, whereas smaller bandwidths result on sharp changes on the distributional values across the study area. The selection of the bandwidth should depend on the objectives of the study (Silverman 1986), as for example smaller bandwidths and sharp changes are the usual choice for identifying ignition hotspots, and larger bandwidths (as for example the mentioned mean random distance), are more adequate for both cause assessment and as base for generation ignition shape files for fire spread simulation. It has to be mentioned, that there are several tools for generating kernel distributions based on points, and some include the possibility to generate polygons or *"isoplets"* that define areas with a defined probability of ignition occurrence, helping to understand the generated maps and ease the task of generating points based on a probability map (Additional B2).

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Additional A

De la Riva et al., 2004 propose the use of kernel methods for estimating the variation in the density of fire ignitions

Mathematically, the kernel density function for n observations can be defined as:

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K(u_i) \qquad \text{Eq. 1}$$

for ui = (x−Xi) / h, where K is the kernel function, h is the bandwidth or smoothing factor, and xi is the value of the observed variables. In the case of point events like ignitions, Xi corresponds to the vector of coordinates of the ignition, and therefore the difference (x − Xi) 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.

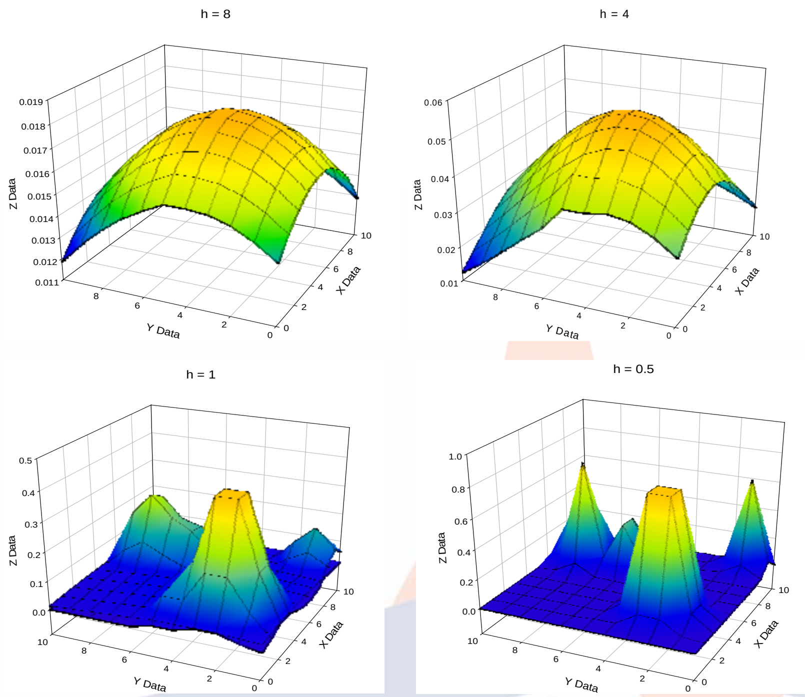
The value for each municipality was the mean of the density function of several sampling points inside the administrative boundaries. In order to account for the variation of number and spatial distribution of fire ignitions, according to their cause the h or smoothing factor varied for each ignition data set. The RDmean value was found to vary substantially according to the ignition cause, and so was used to define the h or bandwidth for the kernel density function for each set of ignitions.

Being RDmean the mean random distance expected for each set of ignitions for the studied municipalities.

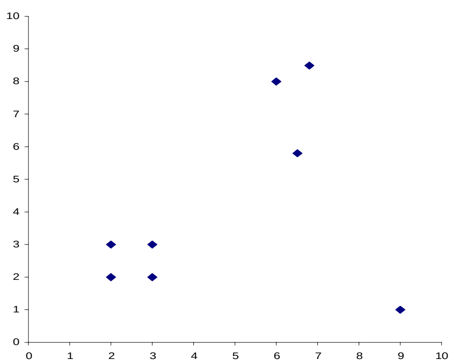
RDmean = 1/2 √ A/N

Where A is the mean size of the municipalities and N are the number ignitions falling in the study area

Additional B1

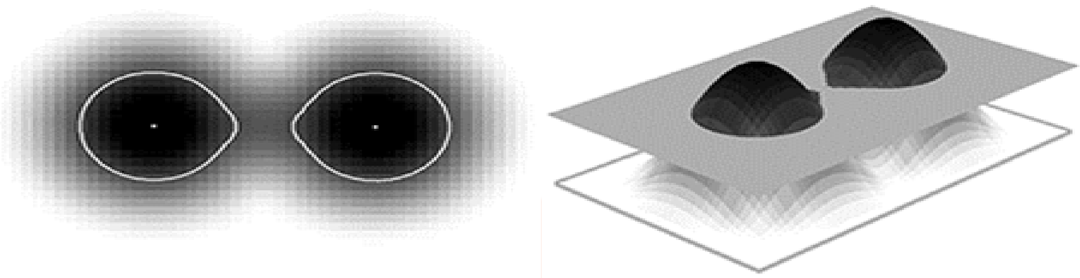


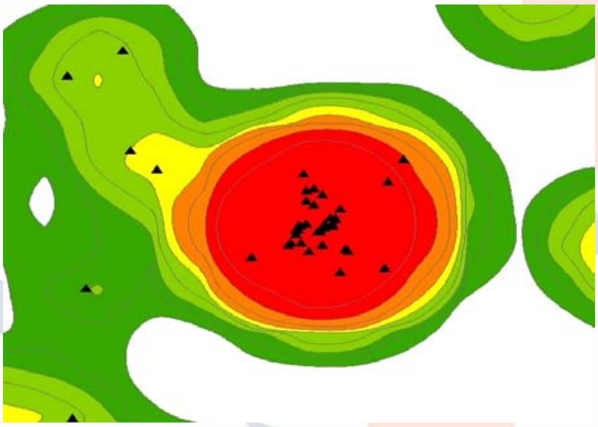
Influence of the smoothing factor selection on the resulting point density distribution, based on the point dataset bellow



X	Y
2,0	2,0
2,0	3,0
3,0	2,0
3,0	3,0
6,0	8,0
6,8	8,5
6,5	5,8
9,0	1,0

Additional B2





Kernel methods produce continuous values of point density across the study area, and using PVC (Percent volume contours) it is possible to generate polygons or isopleths that frame areas with a defined probability of ignition occurrence