Fire Risk Zoning at National Level in Greece: Methodological Approach and Outcome[1]

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Abstract

The focus of our study is to assess fire risk zones using historical wildland fire ignition observations recorded between 1985 and 2004. Kernel density estimation, a non parametric statistical method for estimating probability densities, has been widely used for home range estimation in wildlife ecology. It has the advantage of directly producing density estimates that are not influenced by grid size and localization effects. Furthermore, it produces densities of any shape and analyzes any data distributed multi-modally or non-normally. Under this perspective, kernel density surfaces have been created and reclassified to construct fire zones. Approximately 60 percent of the 10 percent of forest fires occurred between 1985 and 2004, have been recorded within the most dangerous zone. Also, similar percentages have been recorded for the fires of the year 1992 and 2004 that have not been used in the analysis. These percentages differ significantly from the expected ones that arise under a random process (20 percent), since in the proposed zoning system each class corresponds to 20 percent of the total area of the study site.

Introduction

Over the past several years, a trend towards occurrence of extreme natural hazards and disasters is observed directly or indirectly related to wildland fires. Fatal accidents also occur with losses of human lives among the fire fighting personnel and other civilians. Characteristic examples are demonstrated in the United States (2003), Canada (2002-2003), Greece (2000), Australia (2002-2003), and more recently from the large fires occurred in Iberian Peninsula and France (2003-2006). Under this perspective, fire fighting organizations design and implement operational projects to successfully face forest fires for prevention, forecast and suppression. Many factors such as requirements, labor, specialized personnel, availability of necessary means, and usually limited economic recourses compete to optimize such efforts and actions.

Wildland fire risk zoning helps to orient a priori the managers towards the proper actions for civil protection. Fire risk zoning might be a strategic operational advantage for the proper development of a Decision Support System, since such actions can be applied with priority (spatial and temporal) inside the zones of high

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risk. Reduction of the necessary costs and maximization of the benefits and outcomes can be considered. Fire risk zoning based on historical fire observations can contribute further for the proper and documented use and distribution of available resources. The diachronic value of those fire risk zones is a challenge and on the same time a requirement so that to become a real strategic operational tool for prevention and suppression. Moreover, preventive measures and actions can be revised based on the documented fire risk zoning and could be focused more on the high risk zones. Fire risk zones could be one of the basic inputs for the construction of fire risk maps aimed at more reliable spatial and temporal prediction of wildland fire occurrence. Based on the fire risk zoning a better and more justified distribution of the available resources can be achieved for fire prevention and suppression, including efficient monitoring inside these high risk zones.

Due to fire characteristics and logistic problems, the precise detection of the actual ignition points is difficult and the recorded fire ignition locations contain positional inaccuracies. Positional as well as attribute uncertainties may result from factors such as small-scale or inaccurate, non-updated maps used to read the x and y coordinates or large interval resolutions (e.g., coordinates given only in degrees and minutes). In this case the assumption of exact locations, which point-based statistics require, is violated (Jacquez and Waller 2000). If the aim is to explain the spatial pattern of landscape fire regimes and/or the underlying causal factors these inaccurate point records may introduce substantial errors. Especially, if explanatory variables are extracted from other geo-referenced data layers using spatial overlay techniques, these records may lead to serious inaccuracies.

In pattern analysis, very frequently a regular grid of quadrats is superimposed over the event distribution to allow the study of point pattern (Gatrell and others 1996), however, assuming lack of spatial inaccuracies. To overcome problems resulting from superimposing a regular grid of quadrats over a point distribution, a "moving window" of fixed dimensions can be used as an alternative for estimating the intensity at each grid cell. In this case, the intensity at each grid cell is estimated using the number of points falling within the size of the "moving window" centered on each grid cell (Bailey and Gatrell 1995). Kernel estimation is an extension of the "moving window" concept where the fixed-size window is replaced by a three-dimensional function (Gatrell and others 1996).

In our study, fire risk zoning is implemented by using the kernel density estimation that is a well known and explored interpolation method. The basic principle of the proposed methodology is the presumption that wildland fire ignition points do not constitute exact point locations but fuzzy ones that define a broader area, where the actual point location lies inside.

Background

Kernel density estimation, a non parametric statistical method for estimating probability densities, has been widely used for home range estimation in wildlife ecology (Worton 1989; Seaman and Powell 1996; Tufto and others 1996). It has the advantage of directly producing density estimates that are not influenced by grid size and localization effects. Furthermore, it produces densities of any shape and analyzes any data distributed multi-modally or non-normally (Seaman and Powell 1996).

The bivariate kernel density estimator is mathematically defined as (Silverman 1986; Worton 1989; Seaman and Powell 1996):

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left\{\frac{(x - X_i)}{h}\right\}$$

where n is the number of points, h is the smoothing parameter or the bandwidth, K is a kernel density function, x is a vector of coordinates that define the location where the function is estimated, and Xi are vectors of coordinates that define each observation i.

The normal distribution function that has been used in the present study for kernel density estimation is given by the following functional form (Levine 2002):

$$g(x_j) = \sum \left\{ [W_i I_i] \frac{1}{h^2 2\pi} e^{-\left[\frac{d_{ij}^{\,2}}{2h^2}\right]} \right\}$$

where dij is the distance between a point observation (i) and any location in the region where the function is estimated (j), h is the bandwidth which represents the standard deviation of the normal distribution, Wi and Ii represents weight and intensity factors at the point location, respectively.

Two types of kernel methods, depending on whether constant or multiple adaptive values are used for the smoothing parameter over the entire region, constitute the two alternative methods that can be applied in kernel density estimation; the fixed and adaptive method, respectively. In the fixed kernel mode, the smoothing parameter, which is defined in distance units, is constant over the entire area of interest. In the adaptive mode the smoothing parameter, which is defined by using a minimum number of point observations found under the kernel, varies depending on the concentration of point observations. This means that in areas of low concentration the smoothing parameter takes higher values than in areas of high concentration (Worton 1989).

An important issue, however, and rather difficult to define when implementing kernel density interpolation, is the choice of the smoothing parameter of the kernel, both in the fixed and in the adaptive mode. Narrow bandwidths allow nearby observations to dominate the density estimate, while wide bandwidths favor distant locations (Worton 1989; Seaman and Powell 1996). According to Silverman (1986), the choice of the bandwidth depends mostly on the purpose for which the density estimate is used. If the aim is to explore the data and suggest models and hypotheses about them, it would be sufficient to choose the smoothing parameter subjectively by visual inspection.

Materials and Methods

Study area and fire ignition points

The fire database used in this study consists of the fire ignition points that occurred between 1985 and 2004 in Greece (Figure 1). The 20 years database contains in total 22312 fire events with x and y coordinates recorded in latitude and longitude using degrees and first minutes resulting in positional uncertainty of about ±700 to ±925 meters in x and y axes. For data analysis, 90 percent of randomly chosen points (18049 fires) have been extracted from each year, while the rest 10 percent (1996 fires) has been used to evaluate the results. Also, the complete year of 1992 (1643 fires) and 2004 (624 fires) has not been used in data analysis since they kept only for data evaluation. The spatial distribution of the different fire datasets are shown in Figure 1.

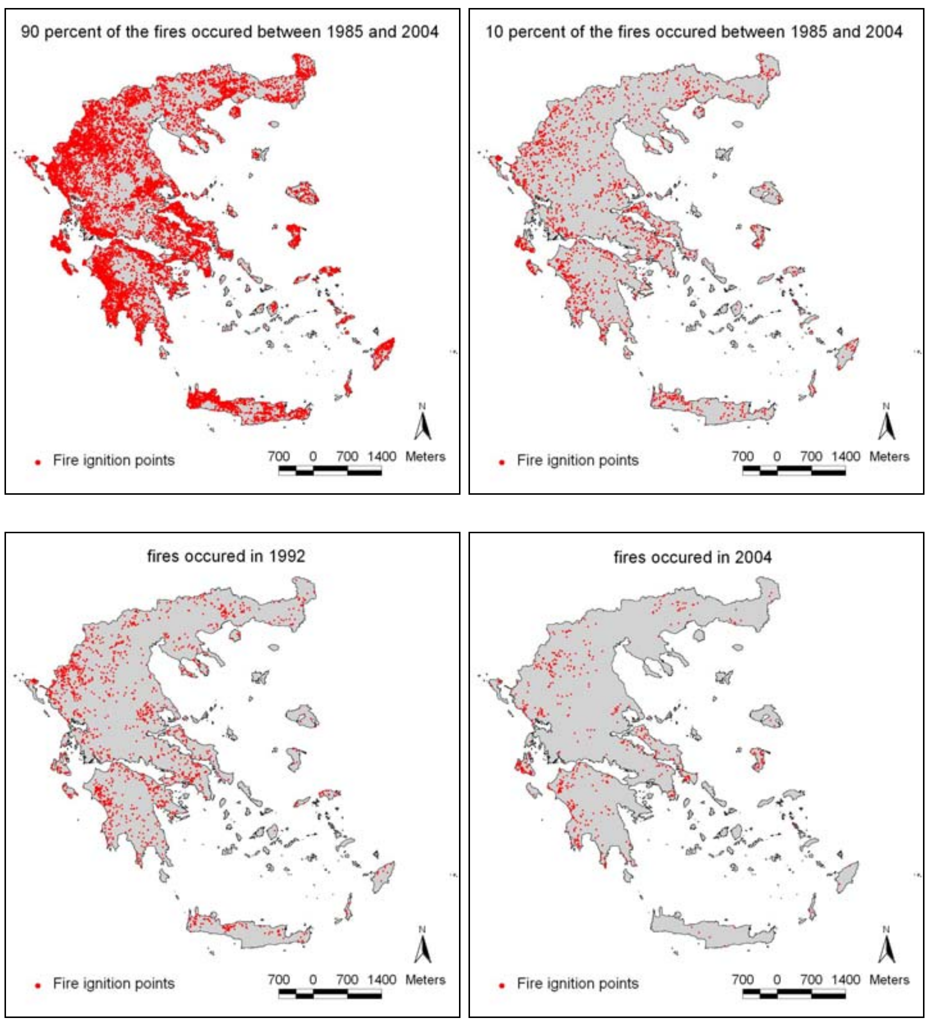

Figure 1 Wildland fire ignition points used for the construction and evaluation of fire zones

Methods

Control points

In general, events may be described either by using a bivariate point pattern consisting of a set of individual observations that correspond to events and control points, or a marked point pattern, where a continuous variable is attached to each individual observation (Gatrell and others 1996). Fire ignition points extracted from historical fire records match none of these two types. The control points are missing, and no continuous variables are attached to each individual observation; only x and y coordinates are extracted from the fire records database. Depending on the anticipated analysis and particularly on the multivariate statistical techniques, however, the fire database containing only x and y coordinates of ignition points is incomplete. To establish a bivariate fire point pattern, control points must be located using a sampling scheme. To avoid creating control points that would be on the same or nearby location to fire ignition points, we applied a random sampling scheme excluding certain buffer zones around fire ignition points. The buffer zones have been chosen based on the first and second mean nearest neighbor distance of fire ignition points. The first mean nearest neighbor distance of wildland fire ignition points equals 1023, while the second mean nearest neighbor distance is 1577. Consequently, random points were generated using a buffer zone of 1023 and 1577 meters for creating two sets of control points and choosing afterwards the one which perform better.

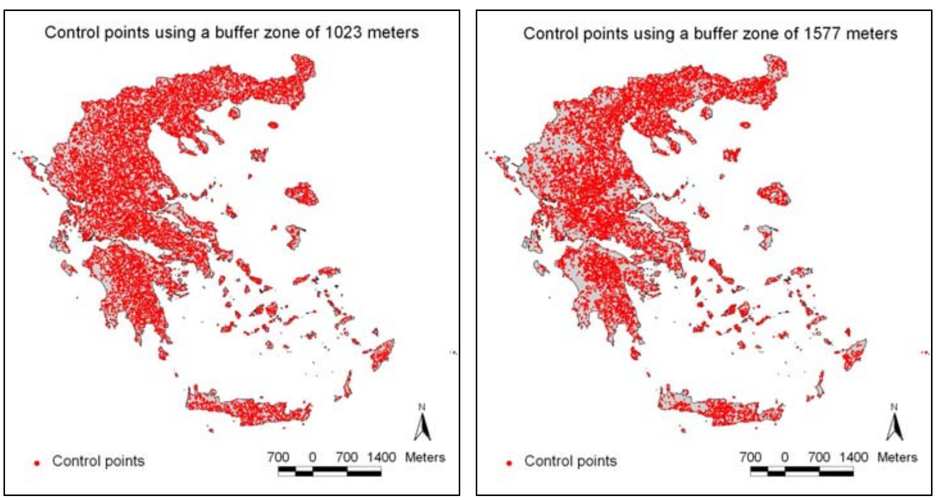

Figure 2 Control points were created using a random sampling scheme excluding, however, buffer zones of 1023 and 1577 meters around fire ignition points.

Also, the mean nearest neighbour distance of fire ignition points was used to estimate the number of control points (Koutsias and others 2004). In total, 18049 fire event records between 1985 and 2004 were retrieved from the Hellenic Forest Service database. The mean nearest neighbour distance of these fire ignition points in the database was 1023 m. This means that fire ignition points represent a clumped spatial arrangement. Under a spatial random process, the mean nearest neighbour distance of 1023 m corresponds to 31540 points across the study area. These 31540 points include both fire ignition points and the control points. Since there were 18049 fire ignition points, there should be 13491 control points (i.e., 31540 minus 18049) so that the control points (Figure 2) and fire ignition points summed together match the random distribution.

Implementing the kernel approach to fire occurrence modeling

To implement kernel density estimation in wildland fire occurrence, the fixed mode approach has been adopted in order to keep the smoothing parameter of the kernel constant over the entire study area. The incentive behind this decision was to avoid different treatments of the point observations over the areas with different degrees of concentration. In addition to the choice of the kernel type, which might not be so important, the choice of the smoothing parameter is very crucial since it controls the amount of variation of the estimates (Worton 1989). To define the size of the bandwidth the mean nearest distance of fire ignition points was considered.

The association of the size of the smoothing parameter of the kernel to the mean nearest distance is reasonable, since the amount of point observations that is going to be interpolated is related to the information content. If the sample size is large, which corresponds to more informative datasets, then a finer interval resolution would be more suitable to avoid over-smoothing and loss of the variability in the estimates. For small size samples, which correspond to less informative datasets, a large bandwidth would be more appropriate, since a fine interval would lead to density estimations that may be perceived as nothing more than a random variation. The size of the smoothing parameter also defines the level of scale of the estimates; large intervals diminish local variability and their estimates are associated with global patterns, while narrow intervals preserve data variability and are associated to local patterns.

Kernel density estimation was applied also to control points established using random design sampling restricted by the constraint of distance. Since, the kernel density estimation of control points refers to points, where no fires have been observed, the estimation was inverted to a negative scale by multiplying the original densities times the value of -1. The inversion to a negative scale preserves the general shape of the data distribution with a mirror effect, however. Finally, the kernel density estimates of both, the fire ignition events and the control points, were combined into one layer using spatial overlay functions.

Results and Discussion

Kernel density surfaces

The constant value of the smoothing parameter of the kernel that has been chosen for the entire study area ensures the same weighting of the point observations over the areas with different degree of concentration. In our study the size of the smoothing parameter of the kernel was based on the mean nearest neighbor distance of fire ignition points. Kernel density interpolation was applied to fire ignition points using three alternative bandwidth sizes of 1023, 1577, and 2014 meters, that correspond to first, second, and third nearest neighbor.

Kernel density estimation was applied also to control points established using random design sampling restricted by the constraint of distance. Since, the kernel density estimation of control points refers to points, where no fires have been observed, the estimation was inverted to a negative scale by multiplying the original densities times the value of -1. The inversion to a negative scale preserves the general shape of the data distribution with a mirror effect, however.

Finally, the kernel density estimation of both the fire ignition events and the control points were combined using spatial overlay functions.

Assessment and evaluation of fire zones

The kernel density surfaces of both, fire ignition points and control points, were reclassified to five classes for creating zones of fire occurrence. The reclassification of the density surfaces was based on the criterion of "equal areas" for each zone. Thus, each fire risk zone corresponds to 1/5 of the total area of the study site. Fire risk zones created by the two different types of control points and the three bandwidth sizes used are depicted in Figure 3.

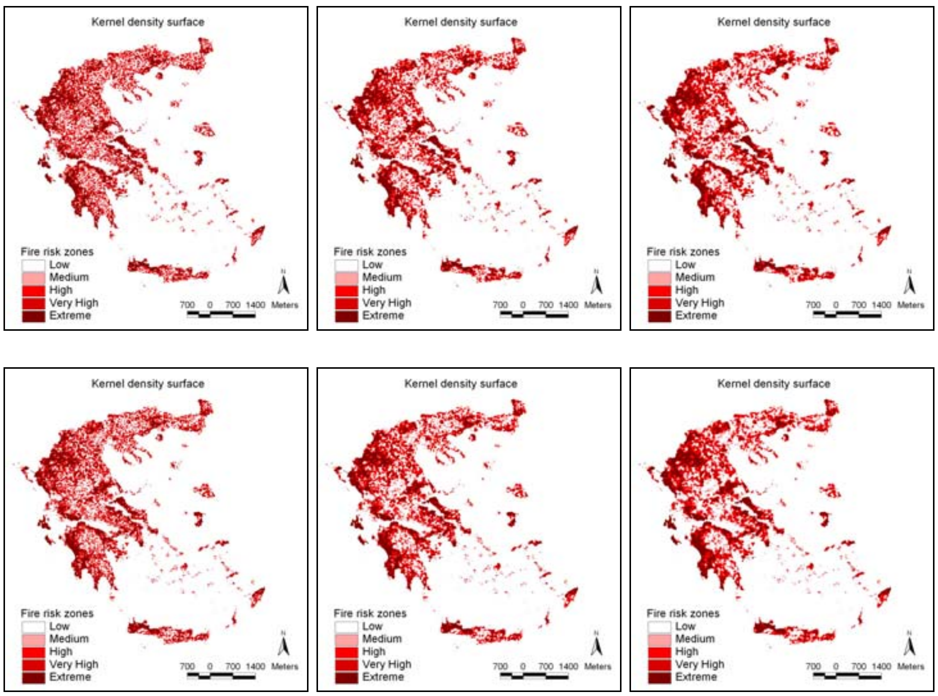

Figure 3 Kernel density surfaces using fire ignition points and control points created using a buffer zone of 1023 meters (upper line of images) and 1577 meters (bottom line of images), and using three bandwidth sizes that of 1023 meters (left column of images), 1577 meters (middle column of images) and 2014 meters (right column of images).

Since, each fire risk zone corresponds to 1/5 of the total area of the study site then it would be expected that fire ignition points occurred under complete spatial random processes would be distributed equal inside each zone. Thus, the expected number of fire ignition points in each zone would be 20% under random processes (Figure 4). Deviations from this expected distribution towards the high risk zones indicates a successful assessment of fire risk zones.

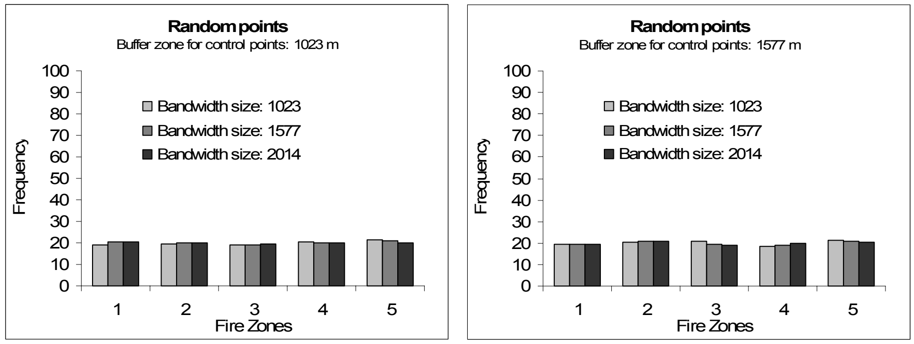

Figure 4 The expected frequency of overlaid points to each fire zone is 20 pct, since each fire zone corresponds to 20 pct of the total area of the study site.

The 10 percent of forest fires occurred between 1985 and 2004, which correspond to 1996 observations, were spatially overlaid over the fire risk zones and the frequency distributions were estimated. Most of fire ignition points (60 percent) coincide to the extreme fire risk zone. Around 80 percent of fire ignition points were corresponded to the two highest fire occurrence zones (Figure 5). This frequency distribution deviates significantly from the expected ones under complete spatial random process and indicates the success of the fire zone assessment. Similar results were observed also when all fire ignition observations of the years 1992 and 2004 were overlaid over the fire risk zones (Figure 6, Figure 7).

Finally, it seems that the bandwidth sizes and buffer zones used in the analysis do not have a very important influence on the assessment of fire risk zones. A smoothing effect is certainly observed when increasing both the bandwidth size and the buffer zone for defining the control points.

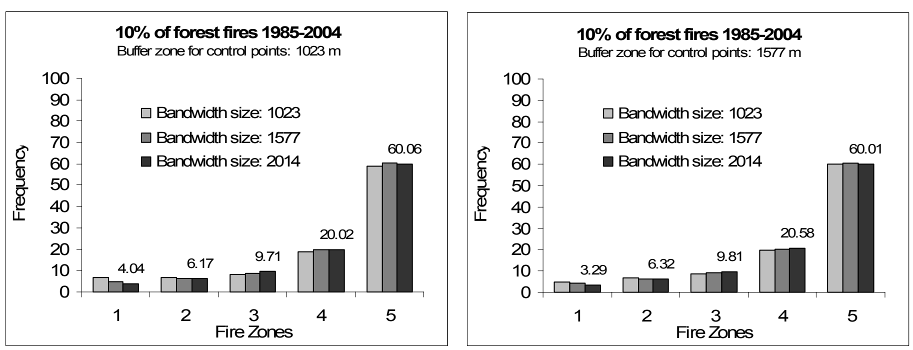

Figure 5 Frequency distribution of the 10 pct of forest fires occurred between 1985 and 2004 to each fire zone.

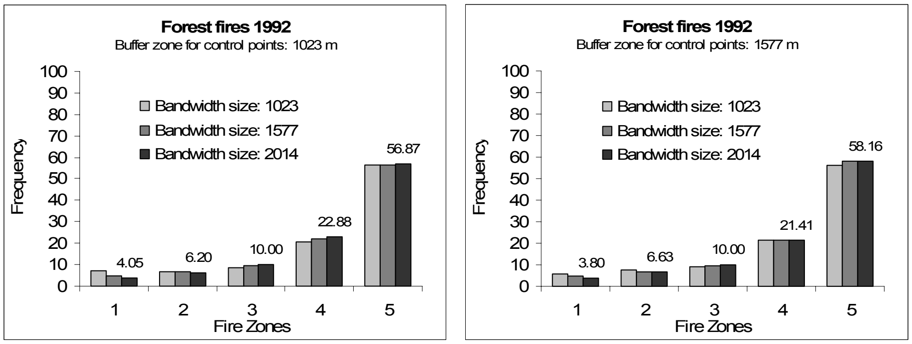

Figure 6 Frequency distribution of the 1992 fires to each fire zone.

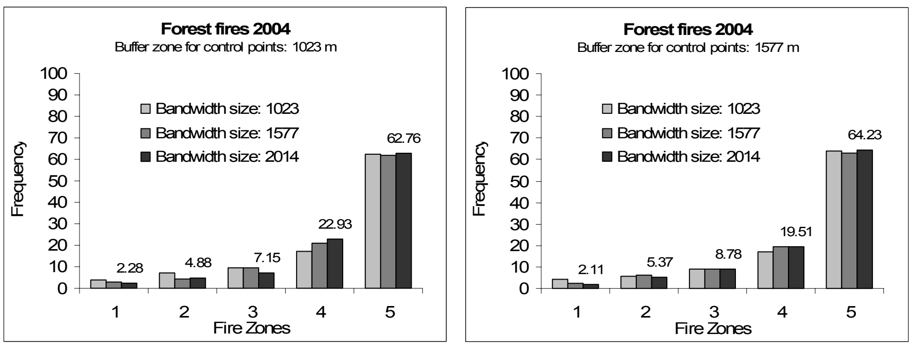

Figure 7 Frequency distribution of the 2004 fires to each fire zone.

Conclusions

Fire fighting organizations design and implement operational projects to successfully face forest fires for prevention, forecast and suppression. Many factors such as requirements, labor, specialized personnel, availability of necessary means, and usually limited economic recourses compete to optimize such efforts and actions. Wildland fire risk zoning helps to orient a priori the managers towards the proper actions for civil protection. Fire risk zoning might be a strategic operational advantage for the proper development of a Decision Support System, since such actions can be applied with priority (spatial and temporal) inside the zones of high risk. Reduction of the necessary costs and maximization of the benefits and outcomes can be considered. Fire risk zoning based on historical fire observations can contribute further for the proper and documented use and distribution of available resources. The diachronic value of those fire risk zones is a challenge and on the same time a requirement so that to become a real strategic operational tool for prevention and suppression.

In our study fire risk zones have been constructed using historical wildland fire ignition observations recorded between 1985 and 2004, based on kernel density interpolation. Approximately 60% of the 10 percent of forest fires occurred between 1985 and 2004 have been recorded within the most dangerous zone. Also, similar percentages have been recorded for the fires of the year 1992 and 2004 that have not been used in the analysis. These percentages differ significantly from the expected one that arises under a complete random process (20%), since in the proposed zoning system each class corresponds to 20% of the total area of the study site.

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