Masters
Program
in **Geospatial**
Technologies

Spatial analysis and investigation of fire events occurrences in the Valencian Community, Spain

Adriana Tanfara

Dissertation submitted in partial fulfilment of the requirements
for the Degree of *Master of Science in Geospatial Technologies*

UNIVERSIDADE NOVA ISEGI

UNIVERSITAT JAUME·I

WESTFÄLISCHE WILHELMS-UNIVERSITÄT MÜNSTER

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Dissertation supervised by

Jorge Mateu, PhD

Department of Mathematics

Universitat Jaume I, Castellón, Spain

Co-supervised by

Pedro Cabral, PhD

Instituto Superior de Estatística e Gestão da Informação

Universidade Nova de Lisboa, Lisbon, Portugal

Edzer Pebesma, PhD

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ABSTRACT

Fires have been affecting on average half a million hectares of forests, shrubland and crops every year. During the second half of the 20^{th} century with socio economic development people abandoned unproductive land and overpopulated more fertile areas and cities. Landscapes started to be covered with natural vegetation or new plantation, often with highly flammable flora (conifers, olive trees, fruit trees, etc.) causing more frequent fire occurrences. Spain follows this trend with high incidence of fires in recent years, underling and emphasising the importance of understanding the causes and spatial distribution of these phenomena. In order to evaluate main characteristics of fires and the distribution of ignitions, 3292 fire events detected in Valencian Community during the period 2000 – 2006 are analyzed. GIS and spatial point process modelling approach are used to quantitatively study the fire effects in relation to variables such as cause, burnt area, proximity to urban areas and roads, population density, land cover and geographic elements. Point pattern analysis was performed using the library SPATSTAT with the statistical package R to determine the spatial intensity of fire ignition distribution and how covariates affect the pattern. Results showed that humans are the leading cause of fires in this region, but as well that the Valencian Community has significant number of lightning caused fires. Fire location are spatially clustered and high fire occurrences was found within areas 1 – 2 km from urban areas and roads, highly populated areas, in agricultural and shrubland cover, lower elevations and tender slopes. Results suggested that there is no simple fire regime for Valencian Community. The Akaike information criterion method is used to select the best inhomogeneous Poisson process model from a set, to best fit the data. The fitted model was diagnosed using simulation envelopes of K function and residual analysis. The model turned out to be inadequate because the fitted intensity function failed to capture the dependence of intensity on covariates. Regardless that a satisfactory model was not found, the study emphasizes the importance of understanding where fires occur and how they interact with socio-economic and environmental factors.

KEYWORDS

Fire occurrences

Geographic Information System

Inhomogeneous Poisson process

Intensity function

R

Spatial point pattern analysis

Valencian Community

ACRONYMS

AIC	Akaike Information Criterion
CLC	CORINE Land Cover
CSR	Complete Spatial Randomness
DEM	Digital elevation model
EDF	Empirical distribution function
EU	European Union
GIS	Geographic information system
HPP	Homogeneous Poisson process
IGN	Instituto Geográfico Nacional de España
SPP	Spatial Point Pattern
UJI	University Jaume I
VC	Valencian Community

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1. Introduction

1.1 Background information

Fires are an integral part of many terrestrial ecosystems, including the Mediterranean ones where they are a dominant ecological factor (Pausas 2001). They affect on average half a million hectares of forest, shrublands and crops every year (Silva et al. 2010). In recent years there has been a significant high trend of number of fires and burnt surface in European Mediterranean areas. One of the most affected regions is Spain (European communities 2004).

There are several important characteristics that make the landscape of Mediterranean Basin (MB) different from those of the rest of the Europe; climate (typically characterized by summer droughts), the long and the intense human impact and the role of fire influenced by the other two (Pausas and Vallejo 1999). Millennia of severe pressure resulting in burning, cutting and grazing non arable land, clearing, terracing and cultivating arable areas have created an area of strongly human modified landscape (Pausas et al. 2008). With industrial development, European Mediterranean countries have faced coastal urbanization, rural depopulation and agricultural mechanization. The Valencian region in Spain succumbed to changes as result of practices such as relocation of the people to the coastal border, farm and grazing abandonment inland, a drift from traditional agriculture to industrial, leading to intensification of agriculture, and tourism economics (Symeonakis et al. 2001, Aguilar et al. 2006). Changes in traditional lifestyles caused progressive land abandonment of large areas which led to the recovery of the vegetation (increase in the cover and continuity of early succession species), but consequently fuel accumulation as well (Houérou 1993, Pausas and Vallejo 1999). Amount and degree of human alteration in the landscape pattern led to changes in the fires regime (Moreira et al. 2001). Beside the human impact, an important factor of increased fire ignition is climate warming having influence on reducing fuel humidity and raising fire risk and fire spread (Pausas and Vallejo 1999, Moreno 2010). As a result those trends make European MB more fire prone.

1.2 Fire ignition modelling

Fires are not randomly distributed: vegetation, climate, topography and human activities determine their spatial pattern (Gosalbo 2006). Fires introduces very different dynamics over large areas with a tendency of differentially geographic occurrences in space, being more frequently repeated in certain topographic location or land cover types (Vázquez and Moreno 2001).

The majority of wildfires in Spain are caused by human activities (Pausas and Vallejo 1999, Calcerrada et al. 2008, Moreno et al. 2010). Fires are an important landscape disturbance which interacts in a complex way with land use land cover changes. During the last three years all the areas burned in the larges EU Mediterranean countries are areas close to or at intermediate distance to roads or towns. Those area burns most frequently (Moreno 2010, Silva et al. 2010). Studies have shown that those variables are significant in determining fire risk. For example, (Calcerrada et al. 2008) found in his research, using the method from Bayesian statistics, the weights of evidence (WofE) model, that spatial pattern of wildfires ignition in south west part of Madrid region were strongly associated with human access to the natural landscape, with proximity to urban areas and roads and one of the most important causal factors. In recent years wildfires risk models that consider other human variables such as distance to recreation areas, air pollution or population density as explanatory variables have become common (Syphard et al. 2007, Tallut and Suding 2008). Using index of topographic roughness and estimates of human population density to model the frequency of fire with regression analysis (Guyette and Dey 2000) verifies that at low population densities fire frequency increases as population density does. Although it is assumed that land use change and human activities in MB is the main reason of the increase in the number of fires and burnt area in recent decades (Pausas 2001, FAO 2006), there are as well other environmental factors (e.g. climate, soils, terrain topography) contributing to the risk of fire ignitions that should be considered.

Several authors (Torn and Fried 1992, Hoffman et al. 2002) have addressed the possible impact of global warming on wildfires using a global circulation model (GCM). Over the years researchers have studied changes in climate and consequent changes in fire hazards in Mediterranean ecosystems as well (Piñol et al. 1998, Pausas 2001). They used correlation and regression analysis to validate the significance of relationships giving confirming results. However, a lot of research is focused on socio economic factors because there are more human caused fires than natural ones. For example, registered lightning caused fires in Spain in the last 50 years were a very few, only 5% of the fires with known cause (Pausas and Vallejo 1999, Moreno 2010).

Many studies have found that topographic elements (elevation, slope and aspect) and fuel characteristics (type, moisture and inflammability) are prominent factors on shaping spatial pattern of natural caused fires (Kushla and Ripple 1997, Vasconcelos et al. 2001, Rayan 2002, Yang et al. 2007). Those variables determine the fire regime by controlling fire spread, intensity and extent (Guyette and Dey 2000). For example, in the (Silva et al. 2010) research elevation positively influenced ignition distribution. It is assumed that this effect may be due to some human activities typical for higher elevation such as renovation of pastures for livestock using traditional burning, which are also known as frequent cause of wildfires in the Iberian Peninsula. On the other hand, (Vasilakos et al. 2009) found that elevations have a small contribution to fire ignitions in Lesvos Island in Greece.

Numerous factors worldwide have been identified as factors influencing the spatial pattern of fire ignitions distribution. However, we can see, the effects of different factors on fire ignition occurrence can vary a lot among ecosystems and across spatial scales (Yang et al. 2007). Findings are different indicating that fire itself is a dynamic complex process that varies in time and space. Driving factors that affect fire occurrence are not evenly distributed in space.

The investigation of ignition causes, ability to understand and predict the pattern of ignition is crucial if we want to understand the important role and relationship between fire regime, weather, vegetation, topography and human activities. It is essential for fire management planning, policy decision and fire prevention. This relationship can be investigated from many perspectives.

A fire modelling method consists of three fundamental components: fire occurrence, fire spread and fire effects (Keane et al. 2004). Field investigation of the cumulative effects would require excessive amount of time and money not available to many fire scientist, thus models are helpful alternative tool used to understand and to predict possible fire behaviour. Fire disturbances can be simulated spatially using either mechanistic or stochastic strategies (Hong and Mladenoff 1999). Mechanistic approach typically focus on a single fire event, while stochastic approaches often focus on multiple fire events over long time periods. Therefore the replication of individual fire events is not a goal of this research, rather the work focus on the large scale characteristics of the historical fire occurrence. The stochastic strategy simulates ignitions randomly or from probability functions of fire starts using vegetation characteristics, climate indicators, topographical setting and/or other parameters as independent variables (Keane et al. 2004). The entire complex ignition process is often modelled using stochastic approaches where the probability of a fire start is approximated from fire history (Johnson and Gutsell 1994, Boychuk et al. 1997), which will be implemented in this work.

Spatial statistical methods make it possible to determine whether or not fires are more likely in some places than in others, and whether fires are more likely to be found in a cluster or at some distance from one another (Podur et al. 2002). One of the techniques is Spatial Point Pattern (SPP) which can be useful in modelling the spatial pattern of fire ignition location as shown in different literature (Podur et al. 2002, Genton et al. 2006, Yang et al. 2007, Hering et al. 2009, Juan et al. 2010). Recent theoretical development within the SPP techniques, such as formal likelihood based methods of inference for a wide range of models, provides tools for statistically rigorous modelling of spatial patterns of fire occurrence (Yang et al. 2007).

The paper presents an analysis of a spatial data set of historical fire occurrence records in Valencian Community (VC) with the intent of quantifying a spatial model of fire distribution intensity. It examines the significance of environmental and social economic factors that may influence the presence and number of fires in VC. Fire ignition is analyzed as a function of topographic elements; elevation, slope and aspect, land use, depicted as well by spatial determinants such as distance to the urban areas and distance to the main roads and population density. These factors will be used as a potential explanation of the spatial variation of ignition density.

1.3 Research objectives and hypothesis

This work focuses on mapping and analysing fire ignition occurrence in VC over the period between 2000 and 2006. The aim of this study was to use GIS techniques for obtaining better understanding of conditions that relate to wildfires ignition variability and the main causes of ignition. Likewise, parametric and non parametric statistical analysis is used with an aim to describe and model spatial point pattern of fire ignition density. Point pattern of fires will be tested against Complete Spatial Randomness (CSR) to see whether data distributions exhibit random, clustering or regularity. Seven independent explanatory variables are used (elevation, slope, aspect, distance to urban areas, distance to roads, population density and land cover), selected due to the possibility of their influence on wildfire ignition occurrence.

The specific objectives of this work are to assess:

1) The pattern and trend in the fire number and area burned, as well as the main cause of fire activities
2) The influence of environmental and human variables on six year fire activities
3) How the intensity of points fire events varies across the study area

In this research it is expected that, due to high human influence over the region and because most of the fires are human caused, locations close to the roads and urban areas should have impact on fire ignition. Although, in the majority of the region population density is relatively low and there is a little variation over the region, it is expected that the higher density of a fire ignition will be found in areas with a higher population density. Land cover was also hypothesized to be an important determinant of fire occurrence as vegetation in the Mediterranean climate region is dominated by woody, evergreen and sclerophyllous shrubs that are very flammable (Syphard et al. 2009) and due to fact that human activities have dramatically increased fire frequency as a consequence of land abandonment and tourist pressure (Pausas and Vallejo 1999). It is hypothesized that topography elements helps to determine the likelihood of fire occurrence as some configurations of the earth's surface are more prone to the fires. With respect to spatial fire distribution it is reasonable to assume that fuel and heat are not homogeneous across landscape, thus it is expected to find a non CSR spatial point process.

1.4 Study area

The Valencian Community is an autonomous community of Spain located in central and south eastern part of Iberian Peninsula. It is situated at 39° 28 N latitude and 0° 22 W longitude geographic coordinates (Figure 1). It covers an approximate area of 23273.439 km^2. Administratively, the VC is divided into three provinces: Alicante, Valencia and Castellón.

The VC today has a population of about 5.1 million people, which represents 10.9% of Spain. The average population density is 219.3 inhabitants per km^2, but with highlighted demographic imbalance, with the majority of the population concentrated on the coastal strip. 53% of the Valencian population lives in the coastal towns (Cámara Valencia 2010). The variation in population density is derived from a traditional concentration of people in localities with fertile cultivation and growing lowlands by the most important rivers (Júcar, Turia, Segura, Vinalopó), as well as harbour cities important for the agricultural trade. In VC land use/land cover change caused by urban growth has affected especially the metropolitan cities of the coastal plains. In these areas the soil is highly productive and can support an intensive and profitable agricultural system (Lozano et al. 2007). The VC has a generally mild climate, heavily influenced by the neighbouring Mediterranean Sea. Proper Mediterranean climate is typical along the coastal plain (518 km), characterized by warm and dry summers and mild winters, changing to continental climate inland. Hot summers and around 100 days of sun per year has influenced on development of a significant beach tourism infrastructure and inland depopulation (Cámara Valencia 2010).

Figure 1: Study area, Valencian Community

Due to its climate, land use history and human activities one of the most fire affected areas in Spain is the Valencian region (Delitti et al. 2004). Extensive grazing is being progressively abandoned as a result of a desertion of the country side to urban centres. Due to lower demand of fuel wood and charcoal there is increasing buildup of fuel in forest and shrub land. Furthermore, the VC is third tourist destination in Spain (Cámara Valencia 2010). All together, fuel buildup and intense tourist traffic has resulted in a steady increase in fire hazards in this region (Houérou 1993).

2. Data preparation

2.1 Analysis tools

Mapping, editing tasks and map based GIS analysis were made using ArcGIS Desktop version 9.3. The main tool for statistical analysis is the open source R environment for statistical computing, version 2.12.0 (The R Project for Statistical Computing). Microsoft Office Excel 2007 was used for computing and tabulation of data. All the data are in shape file format, represented in a projected Coordinate System ETRS89 with Universal Transverse Mercator (zone 30) projection.

2.2 Data

In this study emphasis was directed on territory characteristics related with human presence and activity. In order to analyze spatial distribution and characteristics of fire ignition the following digital cartography were prepared.

2.2.1 Fire ignition

Fire data of VC used for this project are property of Conselleria de Medi Anbient, Generalitat Valenciana which are granted to University Jaume I (UJI) for research purposes. The fire data consist from polygons of burnt areas for the period of six years, from 2000 to 2006. The data contain additional fire characteristics such as cause of the fires and the date of fire occurring. It is considered that the area is burnt only once, thus if there was overlapping between polygons of burnt area preference is given to the more recent fire. From the initial 3309 polygons of burnt area, after geometry cleaning, 3292 fire locations were considered for which area was calculated. To represent an estimated hotspot of a fire ignition, centroids were generated. Figure 2 depicts a map of burnt areas and generated hotspots.

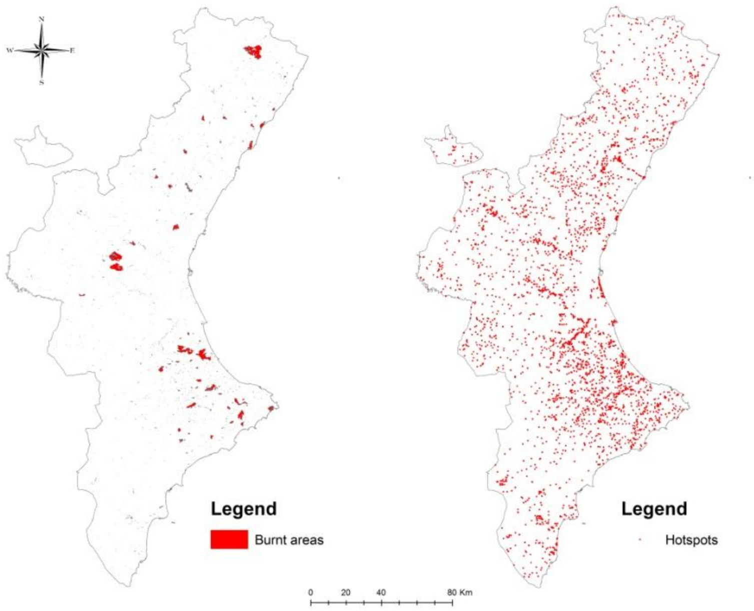

Figure 2: Burnt area (left) and generated ignition hotspots (right) in Valencian Community (period 2000 – 2006)

2.2.2 Land cover

CORINE Land Cover (CLC) cartography inventory for the year 2000 in scale 1:100 000 and with the surface area of the smallest mapping unit of 25 ha was obtained from the Instituto Geográfico Nacional de España (IGN). CLC is a map of the European environmental landscape based on interpretation of satellite images. It provides comparable digital maps of land cover for each country for much of Europe. Land cover classes used for this research are defined based on a CORINE nomenclature (CLC classes). Initially, 44 land cover classes where categorized into six classes: 1) urban and other artificial surface, 2) cultivable land, 3) heterogeneous agriculture, 4) forest, 5) shrub and herbaceous vegetation and 6) wetland and water bodies (Figure 3). The description of class's inclusion and areas statistics are exhibited in Table 1.

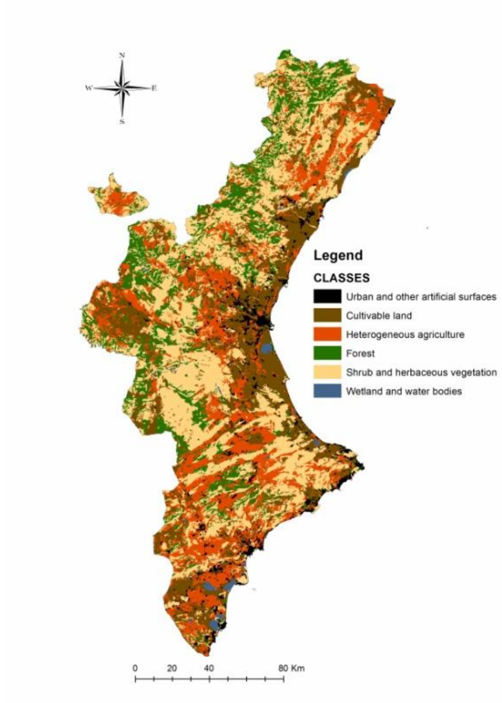

Figure 3: Categorized CORINE Land cover 2000 in Valencian Community

Land cover pattern within the study area have obvious spatial distribution characteristics from sea to inland. Most of the infrastructure and economic activities of the region are concentrated in a coastal zone. Near urban areas, going toward inland, dominates agriculture, mostly cultivable land, extended on 22% of VC land and heterogeneous agriculture around 23.51%. Most represented land cover types of this region is shrub and/or herbaceous vegetation (35.66%). Forest make up only 13% of the cover, mainly inland.

Table 1: Land cover classes based on CORINE nomenclature and area statistics

Code	Land cover class	Area (km)	%	Description
1	**Urban and other artificial surface**	908.96	3.91	Urban fabric, industrial, commercial, and transport units, mine, dump and construction sites and artificial, non agricultural vegetated areas
2	**Cultivable land**	5106.81	21.94	Intensify agriculture; arable land (irrigated and non irrigated land) and permanent crops (vineyards, fruit trees, berry plantation, olive groves)
3	**Heterogeneous agriculture**	5470.74	23.51	Non permanent crops, complex cultivation, land principally occupied by agriculture, with significant areas of natural vegetation, agro-forestry areas
4	**Forest**	3310.7	14.23	Broad leaved forest, coniferous forest and mixed forest
5	**Shrub and herbaceous vegetation**	8299.11	35.66	Natural grassland, moors and heathland, sclerophyllous vegetation, transitional woodland/shrub and open space with little or no vegetation
6	**Wetland and water bodies**	177.11	0.76	Inland wetlands, coastal wetland, inland waters and marine waters
	Total	**23273.44**	100	

2.2.3 Anthropogenic variables

These maps were produced using BCN 200 (Cartographic Numeric Database of Spain Base in scale 1:200 000) for VC obtained from IGN. Specifically, vector shape files of municipalities, municipality's capitals and other settled areas, and roads (motorways, national and autonomous roads). All vector data were overlayed with fire ignition hotspots for analysis in GIS environment (Figure 4).

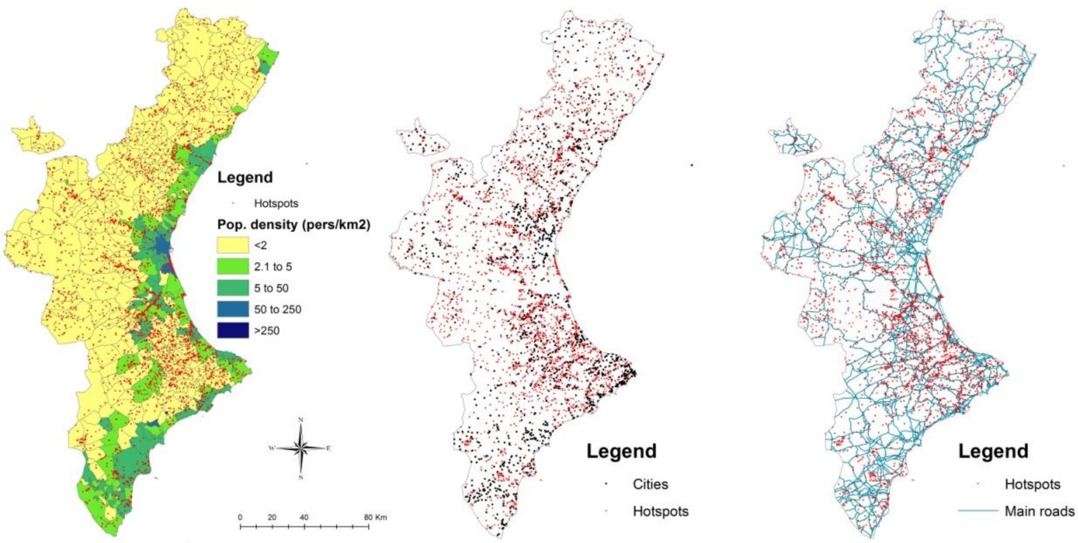

Figure 4: Ignition hotspots superimposed over population density map (left), urban areas (center) and main roads (right)

Population density (number of persons per km^2) was calculated from 2008 census data, the number of persons present in each municipality, using attribute information which was contained in the municipality shape file. These values were divided with corresponding areas. This component of human population density does not reflect changes in population density over time, rather it is static variable and it is assumed no or very little changes in population density over observed period and census data. In 75% of the territory live not more than 2 persons/km^2, however this correspond to just 7% of the VC population.

Using vector shape files (cities and roads) and calculated Euclidian distance, a raster was generated representing distances to urban areas and respectively distance to main roads. From the center of the source cells (urban areas or roads) it was calculated all the distances to the center of each of the surrounding cells. This raster data will be used as inputs in R environment for point pattern statistical analysis (Appendix A).

2.2.4 Topographic variables

Determining the relationship between topographic features of the terrain and fire occurrences is important for evaluating the activities of fire (e.g. the rate and direction of fire spread). In order to analyze fires as a function of topographic attributes a digital elevation model (DEM) of the study area is used. DEM in ASCII format with 200 m spatial resolution was obtain from IGN and converted to raster. Topography is usually broken into following categories which were derived from DEM: elevation, slope and aspect (Figure 5). Elevation and slope are represented as continuous variables, while aspect was reclassified and introduced as factor in nine categories; flat (F), north (N), northeast (NE), east (E), southeast (SE), south (S), southwest (SW), west (W) and northwest (NW).

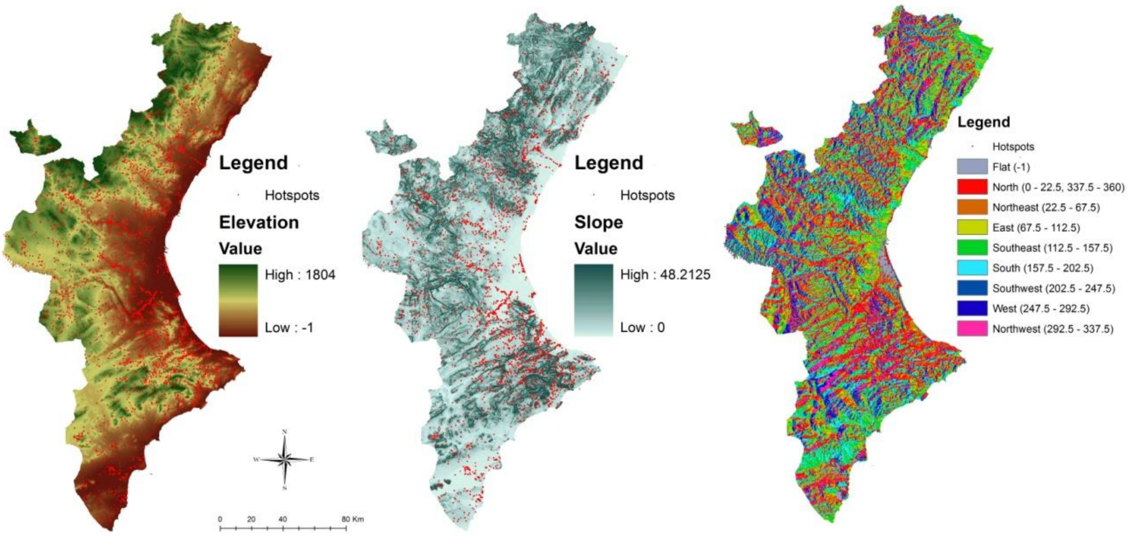

Figure 5: Ignition hotspots superimposed over elevation map (left), slope map (center) and aspect map (right)

From DEM it was observed main characteristics of the study region. The average height of VC is 869.56 m, with minimum of -1 m, maximum of 1804 m of land height and 504.07 m of standard deviation. The slope of terrain varies from 0 to 48.21 degree, but around 79% of the territory have slope less than 10 degree (mean value is 6.15 degree and standard deviation of 5.75 degree). In the terms of the direction the slope is facing more than 25% of VC is facing south and southwest.

3. Methods

This section describes GIS and statistical methods employed to achieve desired objectives in order to explain fire ignition occurrence in VC based on a set of explanatory variables. The entire R code used in the statistical part of the study is presented in Appendix E.

3.1 Analysis in GIS environment

Fires were analyzed a priori purely descriptively to obtain a general view and idea regarding spatial-temporal fire characteristics itself and in context with other variables. All thematic maps were further treated and incorporated into the same GIS environment to create different cartographic overlays and subsequent analysis of a fire regime to make inferences about historical fire activities, and consequently about future ones as well. Based on the data, the relation between fires and landscape, population density and socio economic variability were quantified. Combination of different thematic layers have been undertaken in order to determine the trend of fires, spatiotemporal dynamics observed in the terms of burnt area, number of fires and seasonality and the most frequent burned vegetation types, human activities and terrain characteristics assuming the pre fire conditions.

3.2 Spatial point pattern

SPP is a set of events irregularly distributed within some region and presumed to have been generated by some form of stochastic mechanism (Diggle 2003). These points might represent trees, animal’s nests, cases of disease, fire location or location of any other naturally occurring phenomena. SPP analysis usually starts with hypothesis that events are distributed independently according to a uniform probability distribution over observed region. In point patterns any kind of additional data at every spatial location may be used as explanatory variables (covariates) for point distribution. For the point pattern covariate analysis the study adopted methods proposed by (Baddeley 2008) implemented in R statistical package SPATSTAT (Baddeley and Turner 2005).

3.2.1 Test of complete spatial randomness

The test of complete spatial randomness (CSR) is usually considered as the appropriate starting model for a point pattern (Mateu 2004, Baddeley 2008). A collection of events is considered to be completely spatially random (uniformly distributed over space) if the intensity λ is constant over space and events are neither clustered nor regularly spaced (Podur et al. 2002). A point process which is CSR point process is formally defined as homogeneous Poisson process (HPP). The first basic task in analysing a point pattern is rejection of CSR as it is a minimal prerequisite for any serious attempt to model an observed pattern, as CSR operates as a dividing hypothesis between regular and aggregated patterns (Mateu 2004). First and second order properties are often used for characterization of a point pattern and testing if there is evidence against CSR. Each the property is the focus of different analysis.

3.2.2 First and second order properties

First order properties measure the distribution of events across study area while second order properties describe the covariance between values of the process at different regions in space measuring the tendency of events to appear clustered, independently or regularly spaced (Gatrell et al. 1996).

First order properties are described in terms of the spatial intensity $\lambda(s)$ defining the number of events per unit area at the point s (Diggle 2003). This is defines as following in (Equation 1), where ds is a small region around the point x and Y(ds) refers to the number of events in this small region.

$$\lambda(s) = \lim_{ds \to 0} \left\{ \frac{E[Y(ds)]}{ds} \right\}$$

(Equation 1)

The second order properties, or spatial dependence of a spatial point process involve the relationship between numbers of events in pairs of sub regions within R (Gatrell et al. 1996). It is a measure of how close events are to each other, indicating clustering or regularity. If the point pattern reflects clustering, points will tend to be closer to each other than expected for a Poisson process. Respectively, for regularity points will tend to avoid each other and be farther apart from one another than a random distribution would suggest (Podur et al. 2002). The second order intensity function is defines in (Equation 2).

$$\lambda_2\left(ds_i, ds_j\right) = \lim_{ds_i ds_j} \left\{ \frac{E\left(Y(ds_i)Y\left(ds_j\right)\right)}{ds_i, ds_j} \right\}$$

(Equation 2)

Intensity may be uniform or homogeneous or may vary from location to location (inhomogeneous). If the point process is homogenous, then for any sub region expected number of points is proportional to the area. Hence, the constant intensity λ is expected. However, it is more likely that intensity will vary across area influenced by different factors (Diggle 2003, Baddeley 2008). Until first order intensity is taking into account only the location of events, the second order intensity function depends on the distance between events, not the exact location.

An exploratory tool for examining the first order properties and a classical test for the null hypothesis of CSR is the χ^2 (chi – squared) test based on quadrat counts and Kernel smoothing. As well, several functions based on distance may be used to contrast CSR (Mateu 2004) and for estimating the second order properties.

3.2.2.1 Quadrat counting method

With this approach the study region is divided into sub regions or quadrats of equal area and the number of events in each quadrat are counted. Under the null hypothesis of CSR the number of points in each sub region is independent and identically distributed (equal number of events per region - expected). From a theoretical viewpoint, the quadrats do not have to be of equal area and could be regions of any shape, but the counted number of points for HPP should be proportional to the region. Any choice of quadrats is permissible. It is more useful if we choose the quadrats in a meaningful way. We can define quadrats using covariate information to test whether the point pattern intensity depend on a covariate (Baddeley 2008), which was implemented in this work as well.

The Pearson χ^2 goodness of fit test is a formal test of the null hypothesis that the model is true against a very general alternative that the model is not true. The test is using Pearson residuals validation (Equation 3). If the data is Poisson it will aspire to zero.

$$Pearson\ residual = \frac{(observed) - (expected)}{\sqrt{expected}}$$

(Equation 3)

3.2.2.2 Kernel smoothing

While the quadrat method gives a global idea of sub regions and related intensity, Kernel technique produces a more spatially “smooth” estimate of the variation of the probability density (Baddeley 2008).

This technique uses a moving three dimensional function (the kernel) which weights events within its sphere of influence according to their distance from the point at which the intensity is being estimated (Gatrell et al. 1996). Kernel estimation weights points that are further away less than those that are close. The usual kernel estimator of the intensity function is defined in (Equation 4), where k(u) is the kernel and e(u) edge effect correction.

$$\tilde{\lambda}(u) = e(u)\sum_{i=1}^{i} k(u - x_i)$$

(Equation 4)
.

Kernel density algorithm is implemented in SPATSTAT giving as a result a raster display representing the resulting intensity estimates as a continuous surface. This show how intensity varies over the observed region.

3.2.2.3 Distance methods

The classical techniques for investigating inter-point interaction are distance methods, based on measuring the distances between points. The general approach of methods is to calculate empirical distribution function (EDF) of a point pattern and compare it against theoretical distribution function under CSR. Typically analysis is performed using simulation envelopes. By calculating n number of independent EDF simulation under CSR it is defined upper and lower simulation envelopes, which is plotted against EDF. EDF outside of upper and lower envelopes indicate rejection of CSR (Diggle 2003).

3.2.2.3.1 Empty space distances F

The empty space function F (point to nearest event) of a point process is the cumulative distribution function of the distance e_i from a fixed point in space to the nearest point of each m sample of a point pattern. Inference is typically conducted by comparing theoretical $F_{pois}(t)$ for a CSR with empirical distribution function F(t).

Values $F(t) > F_{pois}(t)$ suggest that empty space distances in the point pattern are shorter than for a Poisson process, indicating regularity, while $F(t) < F_{pois}(t)$ suggest a clustered pattern. The $F_{pois}(t)$ and EDF of empty space distance F(t) are defined in (Equation 5), where # means "the number of" (Diggle 2003, Mateu 2004).

$$F(t) = m^{-1}\#(e_i \leq t) \qquad F_{pois}(t) = 1 - \exp\left(-\lambda\pi t^2\right)$$

(Equation 5)

3.2.2.3.2 Nearest neighbour distances G

The nearest neighbour distance distribution function G (event to event) of a point process is the cumulative distribution function of the distance d_i from a random point to the nearest other point of a point pattern. Interpretation of G(t) is the reverse of F(t). Values $G(t) > G_{pois}(t)$ suggest that nearest neighbour distances in the point pattern are shorter than for a Poisson process, indicating clustering, while $G(t) < G_{pois}(t)$ suggest a regular pattern. G(t) and $G_{pois}(t)$ are given in (Equation 6).

$$G(t) = n^{-1}\#(d_i \leq t) \qquad G_{pois}(t) = 1 - \exp\left(-\lambda\pi t^2\right)$$

(Equation 6)

3.2.2.3.3 Pairwise distances K

Pairwise distances (variously known as the reduced second order moment function or Ripley's *K* function) is a stationary point process so that λK(t) is the expected number of other points of the process within a distance t of a typical point of the process. K statistic use the distances between all neighbours in a point pattern and it is a preferred mean to examine it as it considers all scale. It is defined as (Mateu 2004):

$$K(t) = \lambda^{-1} n^{-1} \sum_{i=1}^{n} \sum_{j \neq i} I(d_{ij} \leq t)$$

$$K_{pois}(t) = \pi t^2$$

(Equation 7)

Values K(t) > K_{pois}(t) suggest clustering, while K(t) < K_{pois}(t) suggest a regular pattern.

3.3 Spatial point pattern modelling

The point process models fitted to the data are often specified in terms of its conditional intensity (Papangelou). Conditional intensity interpret probability of having an event at point u given that the rest of the point process coincides with x (Baddeley and Turner 2000). In practice, the conditional intensity is normally specified through a loglinear form (Equation 8) where θ_1 and θ_2 represent parameter to be estimated.

$$\lambda(u, x) = \exp\,(\theta_1 B(u) + \theta_1 C(u, x))$$

(Equation 8)

The trend term B(u) depends only on the spatial location u, so it represents spatial trend or spatial covariate effects. The interaction term C(u, x) depends beside on the point u and on the configuration of x. It represents stochastic interactions between the points. The term C(u, x) is reduced to zero for the Poisson process (Baddeley and Turner 2000). R software currently fits models by the method of maximum pseudolikelihood.

3.4 Model selection and evaluation

The effective way to choose between a set of models is to use Akaike Information Criterion (AIC). The AIC is a measure of goodness of fit that takes the number of fitted parameters into account (Dalgaard 2008). “True model” does not have to be in the set, the goal is to select the best approximating model of set (Burnham 2004). It is widely used as a measure for selecting the best among competing models for a fixed data set (Yang et al. 2007). AIC is described as in (Equation 9), where k is the number of parameters and L is the maximized value of the likelihood function for the estimated model. The smaller AIC values favours a better fit of the model to the observed data.

$$AIC = 2k - 2\ln(L)$$

(Equation 9)

Although summary statistic such as K function are intended primarily for exploratory purposes, it is possible to use them as a basic for statistical inference (Baddeley 2008). Thus, simulation envelopes of K function were used for testing realization of a finally fitted model, but instead of assumption that the null hypothesis was CSR, the simulated process was generated according to the fitted model, taking into account ihnomogeneity. The inhomogeneous K function supposes non constant intensity at each location of a point pattern, so each point x_i will be weighted by $\omega_i=1/\lambda(x_i)$. The inhomogeneous K function is given in (Equation 10 below (Mateu 2004):

$$K_{inhom}(t) = \lambda^{-1} n^{-1} \sum_{i=1}^{n} \sum_{j \neq i} \omega_{ij}^{-1} I(d_{ij} \leq t)$$

(Equation 10)

As well, residual diagnostic plots, recently formulated by (Baddeley et al. 2005) that plot residual against a spatial continuous covariates, was used as a additional checking or criticising tool of the fitted model.

4. Results

4.1 General characteristics of fire events occurrences

According to the results obtained by the analysis of cumulative fire incidences during the 6 year period around 1% of the VC region has been burned (25323.20 ha). From 2000 to 2006 average burnt surface every year was 7.69 ha with standard deviation of 99 ha. Province Valencia is the most affected with 11717.26 ha of burnt area, followed by Castellon with 7698.80 ha and Alicante with 5907.14 ha. Fires mostly affected shrub and herbaceous vegetation (70.06%) and 14.47% of influenced area were forests (Table 2).

Table 2: Wildfire occurrence related to vegetation cover type

Code	Land cover	Burnt area (ha)	% of total burnt area
1	**Urban and other artificial surface**	129.82	0.51
2	**Cultivable land**	1395.39	5.51
3	**Heterogeneous agriculture**	1781.85	7.04
4	**Forest**	3663.85	14.47
5	**Shrub and herbaceous vegetation**	17740.4	70.06
6	**Wetland and water bodies**	611.89	2.42
	Total	**25323.2**	100

From a total of 3292 fires, small fires (< 1ha) make 70% of fires, however the burnt area of these fires is less than 1% (220.71 ha). The rest of the burnt territory was burnt by fires bigger or equal than 1ha (25102.49 ha). Almost 60% of the burnt area is caused with wildfires bigger than 500ha.

More than 50% of the fires were caused due to human reasons, either deliberate or negligence. This number is greater if we do not consider only direct human caused fires. Agricultural burning, bonfire, smoking, forestry work, grass burning and fires caused by engines and motors rise percentage on human direct and indirect caused fires on more than 65%. Natural fires caused by lightening (ray) make 24% of total fires. Distribution of those natural and non natural caused fires is very different as well. Natural ones are mostly concentrated inland while fires caused by human activities are aggregated in coastline region (Figure 6). Fires were also observed separately through years. It is observed that the amount of burnt area has been decreasing while the trend of number of fires was increasing.

The trend in burnt area and number of fires in each year, as well as cumulative affected areas, different causes of the fires ignition in Valencian region and frequency analysis to investigate where most common fires were ignited are visualised in Appendix B.

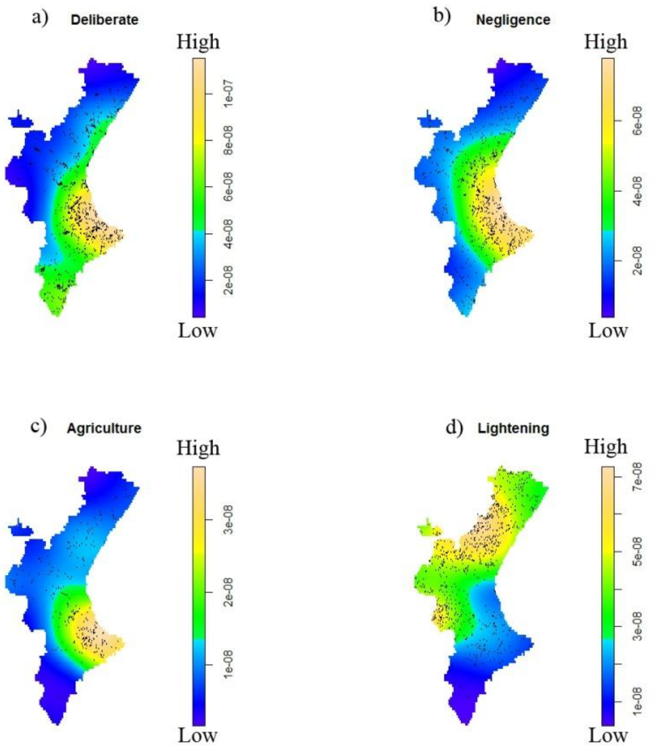

Figure 6: Distribution of fire ignition hotspots caused by human activities, either deliberate (a), negligence (b) or agricultural burning (c) and lightening caused fires (d)

4.2 Fire ignition and covariates

To analyse in which land cover fire mostly occurred, ignition hotspots were superimposed on the CLC. Analysis showed that the fires in almost 60% of the cases started in agricultural land, either cultivable land or heterogeneous agriculture. 31.75% fires started in shrub and herbaceous vegetation. Fires caused by lightening in almost 50% of the cases happened in land cover of shrub and herbaceous vegetation.

It has been explored quantitatively how distance to urban areas, main roads and population density influence fire ignition occurrence. About 39% of fires occurred at less than 500 m from main roads and 84% were within a distance of 2 km. Fire hotspots were also located very close to the urban areas, with 6% at less than 500m distance, and 53% of hotspots at less than 2 km. Most of the fires (72%) that occurred were in areas of lower population density (less than 2 persons per km^2). For map visualization refer to Figure 4.

Furthermore, in relation with topographic characteristics it is observed fire frequency depending on elevation, slope and aspect. Results show decreasing trend of fire frequency with increase of the terrain height. Around 38% of the fires were in landscape lower than 200 m, 57% in areas higher than 200 m, but less than 1000 m and only 4.6% of the fires were in elevations higher than 1000 m. As well, it was observed decreasing trend of fire frequency with increase of the slope degree. Around 79% of the fires happened in the terrain where slope is less than 10 degree, 17.65% where slope is between 10 and 20 degree and only 3% of the fires were in the area with slope higher than 20 degree. By analyzing aspect characteristic and fire occurrence frequency results show that the highest number of fires (more than 40%) were detected in areas most suitable for fires; south (14.70%), southwest (9.75%) and southeast (15.70%). High number of fires (13.91%) was detected as well in the slope facing east. Interaction between fire ignition hotspots with topographic characteristics and land cover is presented in visual form in Appendix C.

In order to model the dependence of a point pattern on a spatial covariates following in next part, all covariates were prepared in raster format and inserted in R environment. Ignition point and the Valencian region were used as well (Figure 7).

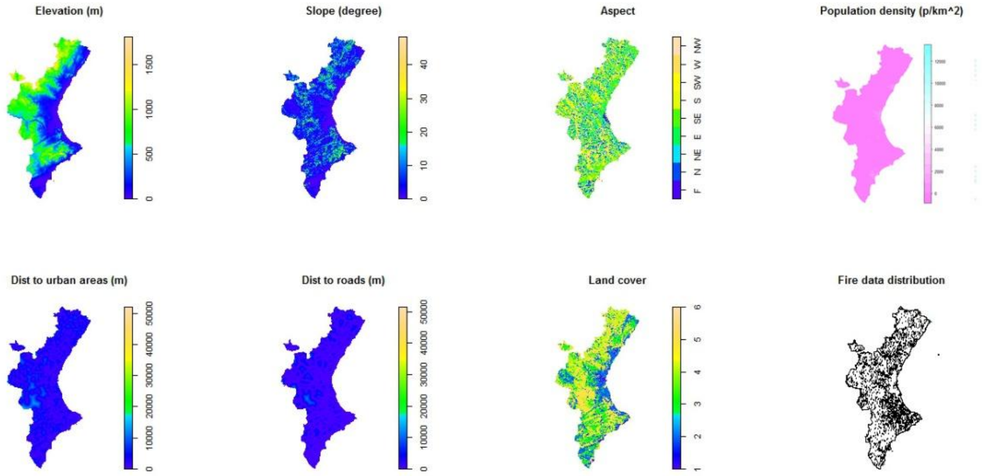

Figure 7: Covariates used for modelling intensity function of fire events distribution

4.3 Test for Complete Spatial Randomness

Fire events in VC for period from 2000 till 2006 have been tested against CSR to see whether data distribution exhibit random, clustering on regularity.

Under the null model of CSR, fire data has a constant intensity of 1.411480e-07 points per square meter over the region of VC. However, in general the intensity of a point process will vary from place to place, thus it is suspected that the intensity may be inhomogeneous. Applied methods of quadrat counts and Kernel smoothing for testing this assumptions, gives a clear conclusion of fire events inhomogeneity.

In quadrat counting the window was divided into 4x4 sub regions, but as well covariates information were implemented for dividing region in a meaningful way. By plotting the objects, qudrats are observed through their observed counts, expected counts and the Pearson residual. If the point process is homogenous, then for any sub region the expected number of points is proportional to the area, which is not the case; the number of points in the sub regions is very different from expected. The other indicator that fire dataset is inhomogeneous is P – value smaller than 0.05 in all of the cases. For clear interpretation all numerical data are shown in the table below (Table 3), while visualization of defined quadrats is presented in Appendix D.

Using Kernel smoothing method it was created fire intensity raster map which indicate concentration of points just in some areas, thus data indicate inhomogeneous pattern From this two visualizing techniques (Figure 8) we can perceive the most risk area is located in a coastal zone (colored yellow hues). Maps of the intensity for all the years (2000 – 2006) are shown in Figure 9. These show the persistent in distribution of hotspots with some minor deviations and in the most risk area.

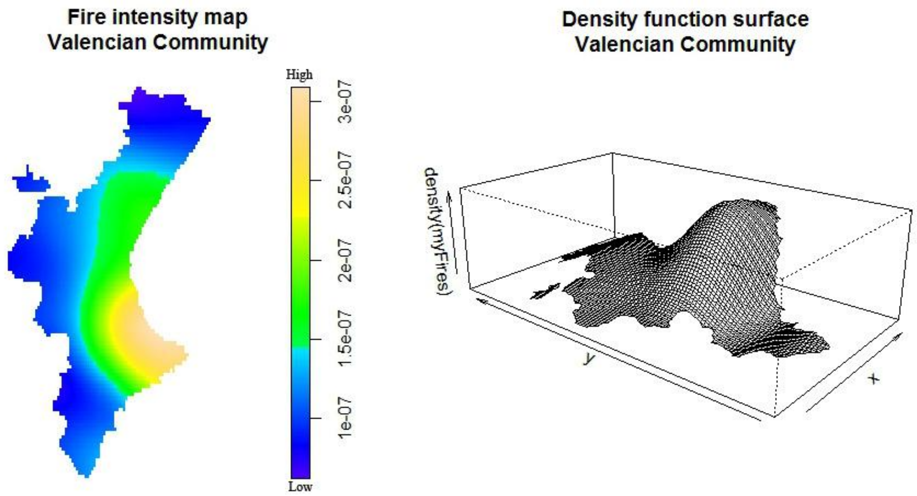

Figure 8: Spatial intensity of fires and corresponding perspective surface for testing CSR

Table 3: Summary results of the quadrat counting method for testing CSR

	Elevation												p-value < 2.2e-16	$\lambda2=371.6536$
	1	**2**	**3**	**4**										
O	1195	954	649	478										
E	817.67	821.93	818.61	817.77										
R	13.19	4.60	-5.92	-11.88										
	Slope												p-value = 0.02298	$\lambda2=9.5337$
	1	**2**	**3**	**4**										
O	744	798	889	820										
E	793.19	819.23	819.28	819.28										
R	-1.74	-0.74	2.43	0.02										
	Aspect												p-value = 2.218e-06	$\lambda2=40.8562$
	F	**N**	**NE**	**E**	**SE**	**S**	**SW**	**W**	**NW**					
O	32	432	432	456	516	484	319	286	326					
E	26.23	354.73	405.92	495.23	604.70	488.99	340.19	266.50	300.47					
R	1.12	4.10	1.29	-1.76	-3.60	-0.22	-1.14	1.19	1.47					
	Population density												p-value < 2.2e-16	$\lambda2=227.4573$
	1	**2**	**3**	**4**										
O	594	633	958	1097										
E	822.77	823.33	819.48	816.41										
R	-7.97	-6.63	4.83	9.82										
	Distance to urban area												p-value < 2.2e-16	$\lambda2=362.8808$
	1	**2**	**3**	**4**										
O	1233	885	646	510										
E	819.25	826.50	808.14	820.09										
R	14.45	2.03	-5.70	-10.82										
	Distance to roads												p-value < 2.2e-16	$\lambda2=229.2226$
	1	**2**	**3**	**4**										
O	862	900	658	493										
E	634.68	758.54	723.51	796.25										
R	9.02	5.13	-2.43	-10.74										
	Land cover												p-value < 2.2e-16	$\lambda2=161.4492$
	1	**2**	**3**	**4**	**5**	6								
O	138	783	800	414	1065	84								
E	128.10	720.14	771.06	467.27	1172.31	25.09								
R	0.87	2.34	1.04	-2.46	-3.13	11.75								
	4x4 quadrats												p-value < 2.2e-16	$\lambda2=688.6553$
O	13	41	326	95	227	491	327	100	520	778	31	5	276	55
E	21.64	41.55	454.47	143.69	345.39	499.48	233.72	112.53	516.79	355.78	19.91	15.58	399.06	49.34
R	-1.85	-0.08	-6.02	-4.06	-6.37	-0.37	6.10	-1.18	0.14	22.38	2.48	-2.68	-6.16	0.80

O - observed, E - expected, R - residuals

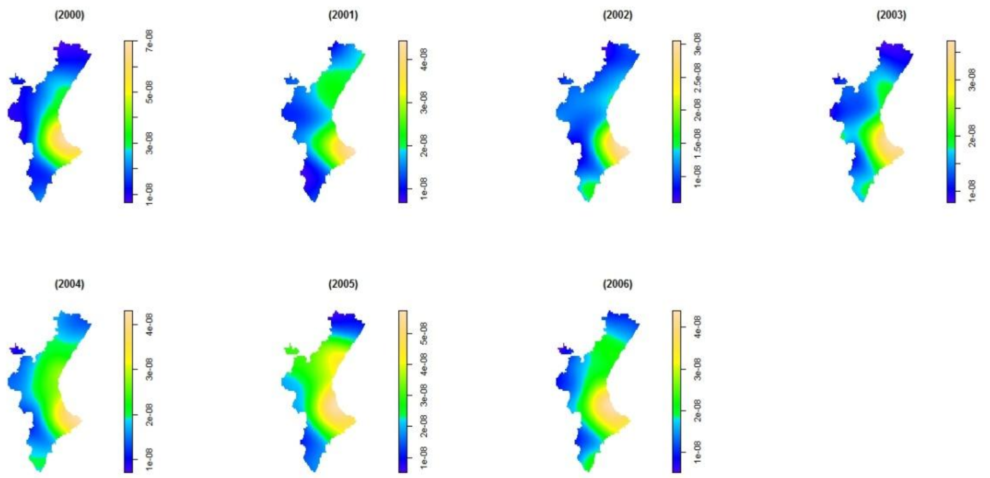

Figure 9: Spatial intensity of fires, temporal evolution for the years 2000 – 2006

Like mentioned in methodology part, a good way for inferring if the point pattern is completely random or there is some spatial pattern is using the distance statistic. The comparability of a point process with CSR is assessed by plotting EDF against the theoretical expectation assuming CSR. For simulation 19 independent EDF under CSR were chosen (Figure 10). In both cases, empty space and nearest neighbour distances, EDF lies outside of simulated envelopes indicating rejection of CSR. Further, plotted EDF of nearest neighbour distances is larger than all 19 simulations, showing excess of small nearest neighbour distances which is a characteristic feature of clustered pattern. Similarly, EDF of empty space distances below the lower simulation envelope typifies cluster pattern as well.

Effective diagnosis of independence or dependence between points includes the K function as well (Figure 11). How EDF is outside of simulated envelopes and pairwise distances are smaller than expected under CSR, pairwise distance statistic indicate inhomogeneous and clustered pattern, as in the two previous techniques.

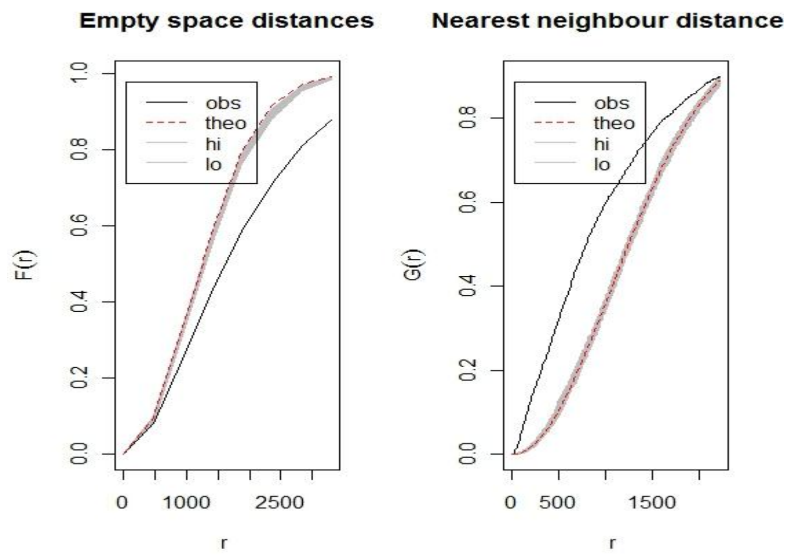

Figure 10: EDF plot of empty space and nearest neighbour distances (solid curve); upper and lower envelopes from 19 simulation of CSR

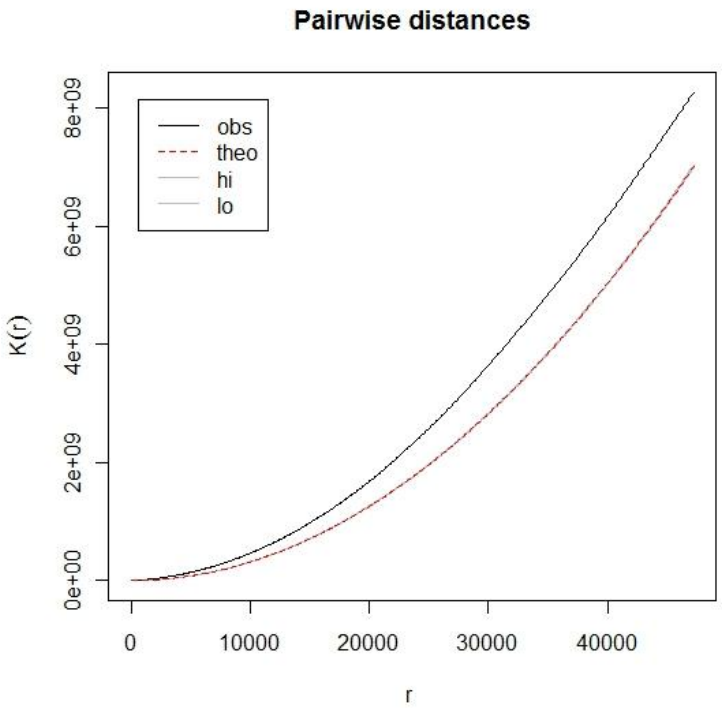

Figure 11: EDF plot of pairwise distances (solid curve); upper and lower envelopes from 19 simulation of CSR

4.4 Model fitting and goodness of fit

Because the fire events did not fit into the null hypothesis that the distribution is homogeneous Poisson the possibility of an inhomogeneous Poisson process was explored with an intensity function that could be explained with spatial covariates that were revealed to affect fire occurrence pattern; elevation, slope, aspect, population density, distance to urban areas, distance to roads and land cover. All possibilities, taking into account all possible combinations of covariates, accurately 127 models, was fitted to date. The final model was chosen based on the lowest AIC value (AIC=107715.0). The best model among those investigated, was a function of all seven covariates. Coefficients for intensity function are given in Table 4. Variables with positive coefficients have positive contribution to the fire occurrence density and negative coefficients have negative contributions.

Table 4: Coefficients of the predictor variable of the final fitted model

Fire ignition occurrences intensity function				
Trend formula		exp(~el + sl + factor(as) + du + dr + pd + factor(lc))		
Intercept				
- 15.82745				
Elevation				
- 0.001013557				
Slope				
+ 0.02421431				
Aspect				
+ 0.4816883 (N)	+ 0.4354635 (NE)	+ 0.3198927 (E)	+ 0.2056588 (SE)	+ 0.3498161 (S)
+ 0.3600464 (SW)	+ 0.5581428 (W)	+ 0.5039866 (NW)		
Distance to urban areas				
- 0.00013887				
Distance to roads				
- 0.00008669166				
Population density				
-0.00027228				
Land cover				
+ 0.3374982 (2)	+ 0.3604987 (3)	+ 0.5843269 (4)	+ 0.4698501 (5)	+ 1.397223 (6)

el – elevation, sl – slope, as – aspect, du – distance to urban areas, dr – distance to roads, pd – population density, lc – land cover

In order to test if suggested model for the intensity is a good representation of the fire events that occurred in VC, 50 envelope simulations of the inhomogeneous K function were generated according to fitted model (Figure 12). By using the inhomogeneous K function the assumption of an underlying homogenous point process is removed while still assuming isotropic stationarity (Hering et al. 2009).

The plot suggests that after accounting for dependence on covariates, the fitted model is not the best possible interpretation since observed function in some parts lies outside of the simulated envelopes. Model failed to capture dependence of intensity and covariates for distances between 2.5 and 9 km and bigger than 35 km. Comparison of simulated model and real fire distribution is shown in Figure 13, giving a clear indication of an inadequate model.

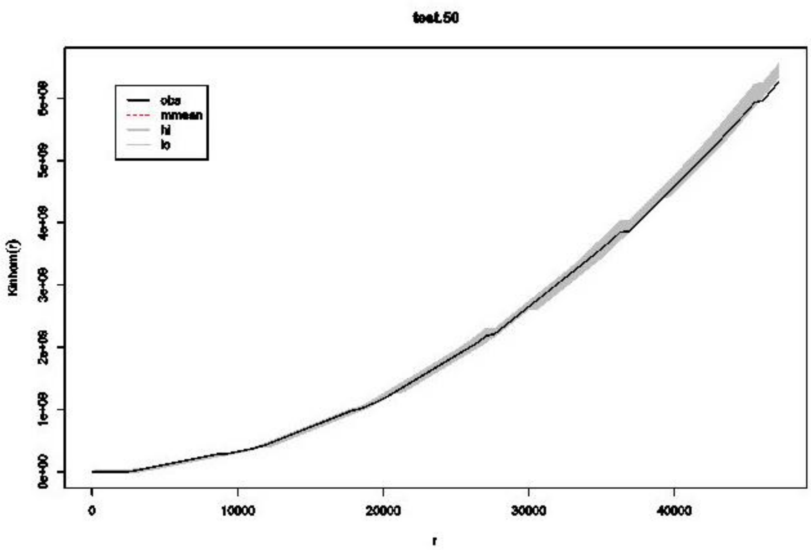

Figure 12: EDF plot of inhomogeneous K function; upper and lower envelopes from 50 simulation of inhomogeneous Poisson process

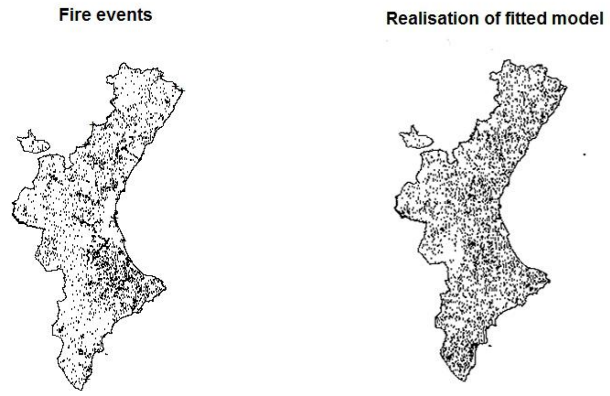

Figure 13: Comparison of fire events in VC (left) and fire events predicted by fitted model (right)

Diagnostic plots and residuals are a useful tool for a quick indication of departure from the trend in the model and the covariate effect (Baddeley et al. 2005). Residuals are plotted against the covariates and Cartesian coordinates to assess how the true spatial trend differs from one specified by the fitted model. For the spatial covariate defined at each location evaluated residual should be approximately zero if the fitted model is correct. Diagnostic plots (Figure 14) suggest that the fitted model underestimated the intensity regarding to all continuous covariates. Take the elevation as an example (Figure 14a). The cumulative Pearson residuals are much less than $+2\sigma$ limit of error bounds for elevations between 100 - 200 m and 600 - 750 m, suggesting that the model overestimate intensity of fire occurrences at this scale. There are less fires occurring at those spatial locations than fitted model predict. Residuals much higher for elevations around 200 – 250 m and bigger than 14 km suggests that there are more fires at this scale. The steepest increase is between 100 - 200 m and 700 m – 1 km indicating that highest number of fires is ignited at those elevations. Respectively, the peak in Figure 14b occurs for slopes of about 2.5 degree and the steepest increase occurs within range of slopes of 2.5 – 8 degree, suggesting that more fires occur on gentle slopes than steeper ones. There is less fire at mild slopes (< 10 degree) and more fires at steeper at spatial location then fitted model predict. Figure 14c shows that there is more than average number of fires within all areas with higher population density. The peak is at about 2 indicating that most fires occur within an area of low population density. The fitted model has deficit of fire events for the distances lower than 3 km and excess for distances approximately between 4 and 8 km from the urban areas. In other words, there are more fires occurring at spatial locations near to roads then fitted model predict (Figure 14d). There is a steep increase of cumulative residuals after the nadir point (1 km) suggesting that most of the fires were ignited at this scale. The lurking plot for distances to the roads (Figure 14d) has similar behaviour as the plot for distances to urban areas indicating that most fire ignition at distances 1 – 2 km from roads.

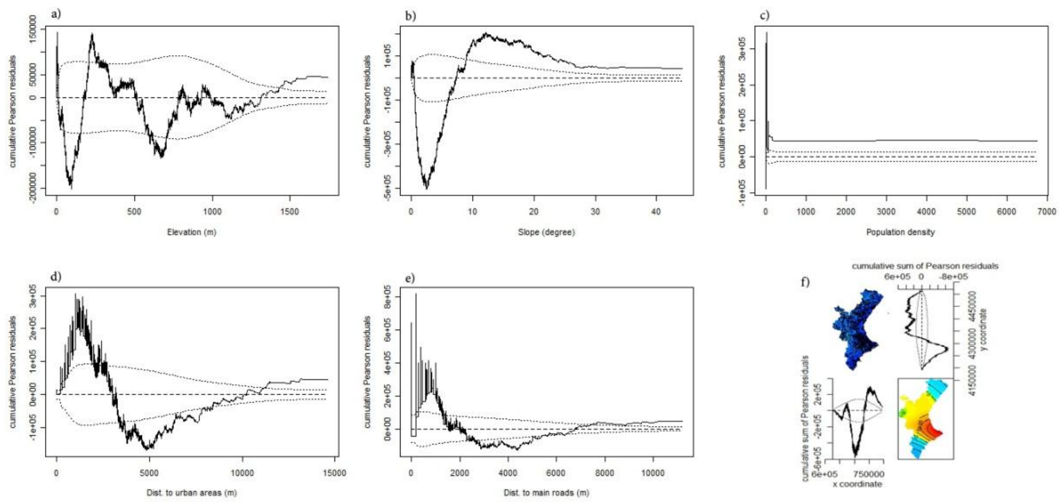

Figure 14: Residual lurking plots of continuous covariate effects and diagnostic plot for spatial trend (four panel plot)

5. Discussion and recommendations

Fire events observed in VC confirm statistics of the Center for Fire Research (Moreno 2010) that despite the increase in fire prevention and suppression effort, as well as a decreasing trend in burnt area, during the last decades the number of fires have continued rising. Probably the reason why fires started to be more frequent is because of rural exodus and changes in life style which little by little accumulated the vegetation fuel (Pausas and Ramos 2004). Particular caution should be directed to forest fires as a second most affected cover in VC. The dynamics of recovery of abandoned agricultural land toward forest, employing new technologies which use great amount of fossil energy made the newly established ecosystem probably generally fire prone (Ales et al. 1992). The facts that certainly does not help are also new trends of more people living in urban forest interface and recreational activities increased in forested areas (Calcerrada et al. 2008, Silva et al. 2010). As fires tend to transform during the initial stages forest to shrubland and shrubland invasion is a much quicker than that of forest, threat of increased fire frequency in those areas is present. It is confirmed that herbaceous vegetation in many Mediterranean agricultural areas is easier to ignite and the fires propagate more easily than in other fuel types.

Comparing density of fire events obtained from quadrat with Kernel density technique both show more dense concentration of fires in the area that follow coast of VC and gradually decreasing going away from the central coastal region toward the heartland. From the summary table of the quadrat method, as well supported by GIS analysis, we can observe how covariates interact with fire distribution. Distribution of fire data in VC is not random. There is obvious inhomogeneous pattern with a strong preference of fires for lower elevations, mild slope facing high potential solar isolation, higher population density, proximity to urban areas and roads, agricultural land and shrub or herbaceous vegetation. The K(t) function, and the two nearest neighbour distribution function, (F(t) and G(t), provided complementary tools for the description of SPP indicating clustering of fire events. The number of simulated envelopes was different in the cases of testing rejection of

CSR and for testing fitted model. EDF under the CSR showed clear results using 19 envelopes, which was not the case with simulations of the inhomogeneous K function according to fitted model, thus it was used 50 simulations. The reason was also long computation time.

Although the proposed model is inadequate because the fitted intensity function failed to capture the dependence of intensity on covariates, all variables included in this research should be incorporated in a trend. Lurking variable plots are helpful to indicate whether or not the presence of a particular variable is needed in the model (Hering et al. 2009). If cumulative residual function of the residuals against variable of interest lies outside of the envelope, this is evidence that the variable should be included in the trend for fitting the model. All covariates in earlier presented lurking plots are partly outside of the envelopes.

How a minimum 50% of the fires in VC were caused by humans, all these types of fires should be clustered around areas where people live, work and recreate, which is confirmed in the Figure 6. Because humans caused the majority of fires, the measure of accessibility represented as a distance to urban areas and roads is an important explanatory factor reflecting the effect of human activities. It was found that the SPP of ignition is associated with landscape accessibility in this area. Distances around 1-2 km of urban areas and roads are the peak of ignition findings and generally associated with higher fire occurrences probabilities. Studies have already showed that these factors are significant in determining fire risk, but as well contrary to what may be believed, areas at intermediate distance to towns or roads might burn in higher proportion than those closer (Moreno 2010).

Land cover, in terms of presence and impact of humans, showed a strong influence on the probability of fire ignition, similar to other author's findings (Lloret et al. 2002, Silva et al. 2010). Significant number of fires occurred in agricultural areas indicating importance of this factor on influence of fire starts. As VC has strong agricultural community, land management such as burning agriculture residues, land burning for pasture renovation or use of machinery, including land cover as basic factors in explaining fire ignition and propagation is crucial.

Although most of the fires were found in the territory of lower population density, compatibility of the densest ignition locations and high population density areas confirmed influence of this factor. Specific spatial pattern of population density with high concentration of people on only 24% of the study region, with discontinuity of the density can be consequence of difficulties to incorporate this variable in the intensity model. From lurking plot we can see that the model overestimated fire events almost 100% regarding to population density.

Elevation and slope negatively influenced ignition distribution in VC. The effect may be due to fact that humans inhabit more accessible and fertile areas which in the VC correspond to low elevations and mild slope.

By plotting the residuals against the Cartesian coordinates (Figure 14f), explanatory variables that were not included in the model, including surrogates for unobservable factors (Baddeley et al. 2005, Yang et al. 2007), the spatial trend showed difference from the one specified by the fitted model. It suggests that to predict the fire regime there can be some other omitted factors such as climate change, fuel management and increased prevention, which could also be important and considered as they can show effects in different direction. Likewise, fires caused by different sources may respond differently (Yang et al. 2007). Consequently, it will be appropriate to analyze them separately.

Since lightning is a natural phenomenon it may be expected that those caused fires should act independently. Despite previous findings that lightning fires in Spain make just a little percentage of all fires, VC showed different pattern. As (Vilar et al. 2010) pointed out, in Mediterranean countries most fire ignitions are due to human activities, but nevertheless lightning is still an important fire ignition source in some regions. Lightning caused fires represents 24% of all the fires in the VC and in the almost 80% of the cases were started in a forest and shrub or herbaceous vegetation cover. Propagation of this type of vegetation and the area of highest risk of lightning caused fires is mostly clustered in the northwest part of the Valencian region (Figure 6, right). Most of the forest and shrubland areas of this region are the result of old field abandonment or afforestation activity. Trees and shrub sprouters have been historically eliminated and after fires shrub obligate seeders species are most frequently found (Alloza and Vallejo 1998). This made shrubland community significantly extended over the years. Shrub land cover is typically dry and prone to accumulation of highly volatile fuels resulting in high combustibility and a natural fire risk (Baeza et al. 2002). This pattern of lightning caused fires clustered in the north-eastern part of the region it can be explained as well due to high frequency of dry storms inland in early summer typical for Eastern Spain (Pausas and Vallejo 1999). Considering all this facts, collection of fuels in the landscape and lightning frequency variables maybe could supplement the inadequate model suggested in this study. It is worthwhile to note that high lightning fire activities do not coincide with the areas of high population density nor lower elevations, both prone to human caused fires. They usually occur in more isolated and steeper areas (Chuviec et al. 2010), so one more doubt why the model turn out to be inadequate.

Thus, it will be appropriate to analyze human and natural caused fires separately as multitype point pattern, as they were showed to be equally important and very differently distributed. Beside variables included in this research it is believed that information related with fuel moisture content, climate and lightning frequency as additional explanatory factors could be helpful in order to estimate appropriate intensity that may explain integrated fire occurrence in the VC.

6. Conclusion

This research analysed spatial structure of fire ignitions in VC in Spain. Beside GIS techniques for quantization SPP analysis was used. Quadrat counts and Kernel smoothing method were apply as the foundation for rejecting CSR and distances methods for inference if there is some sort of spatial trend in frequency of fire events. It was found that fire events tend to be clustered and the intensity of the point process varies over the region. Potential inhomogeneous Poisson model using additional covariates information for explaining spatial variation in the distribution of fire events was also investigated. Examined variables, elevation, slope, aspect, population density, distances to urban areas, distances to roads and land cover were showed to be needed for determination of intensity, but not sufficient for explaining inhomogeneous process in Valencian region. Results showed that ignitions caused by human and lightning are the leading causes of fires in VC, but because their very different spatial occurrences it is suspected that the proposed model failed to capture dependences of fire events and observed covariates. The work proposes for the future research segregate analysis of those incidents.

Understanding about why, where and when do fires starts is essential for deriving appropriate fire policies management. It is important for both biodiversity conservation and the protection of life and property. The map of fire occurrence can be directly used to point out areas that should be considered as risk categories and consequently facilitate protection. Although in this work appropriate estimation of fire intensity was not reached, this work has addressed the importance of the ability to understand and predict the patterns of fire ignitions which will help managers and decision makers to improve the effectiveness of fire prevention, detection and fire fighting resources allocation. Thus, we should strive to explore more in order to understand fire events occurrences.

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APPENDICES

Appendix A: Anthropogenic variables (raster)

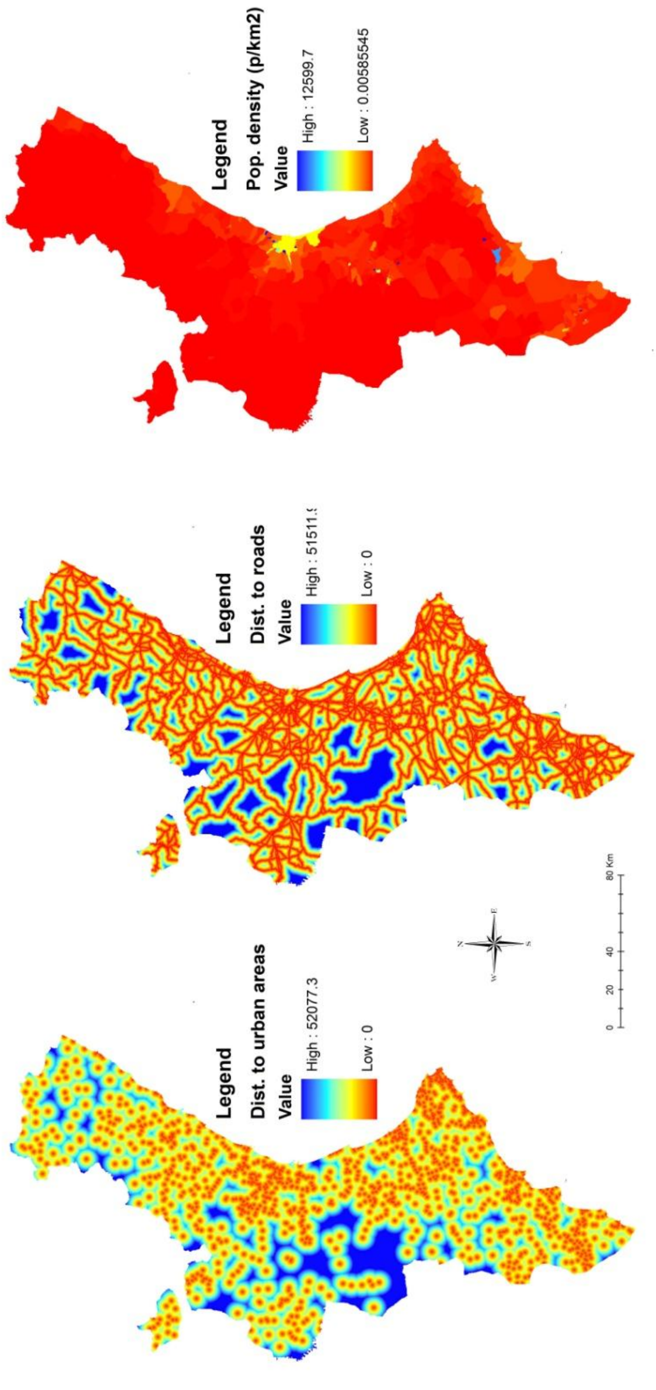

Figure 15: Calculated Euclidian distances (distance to urban area and main roads) and population density

Appendix B: Fire characteristics

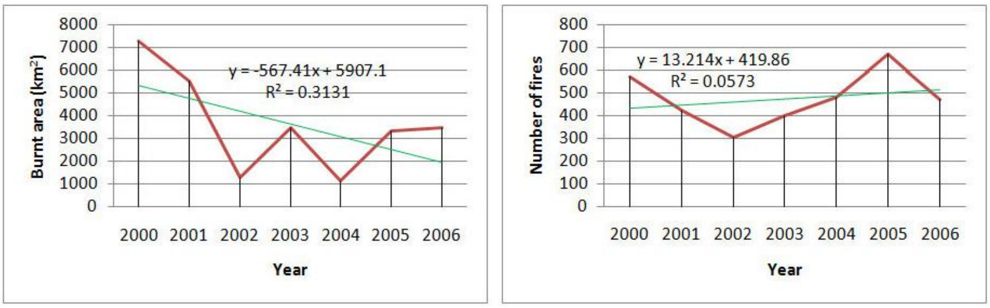

Figure 16: Trend in burnt area and number of fires in the period from 2000 to 2006

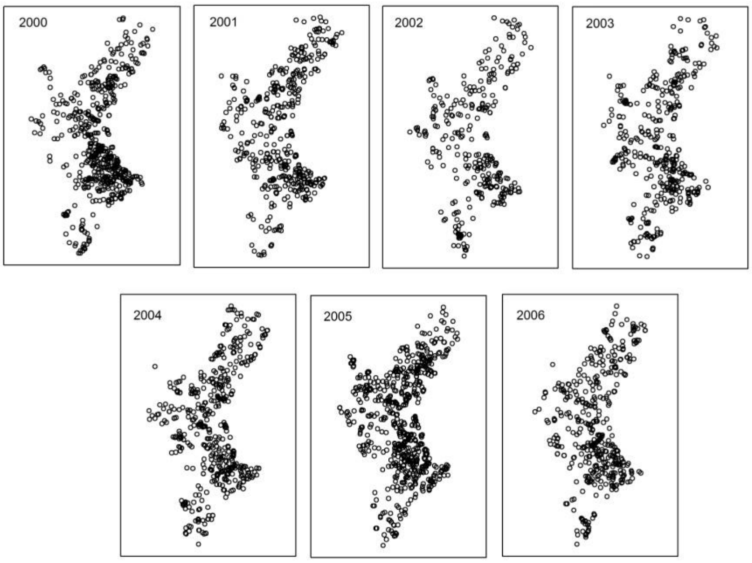

Figure 17: Distribution of the fire hotspots over the years

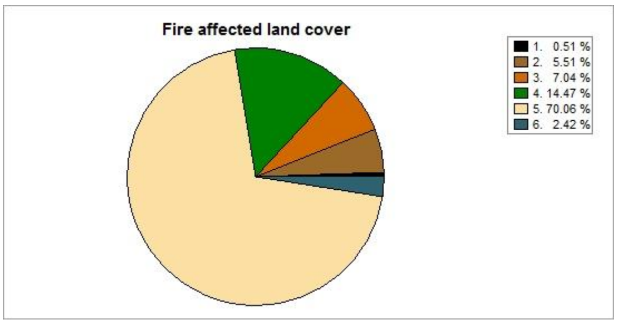

Figure 18: Proportion of land cover damaged in fires in period between 2000 and 2006

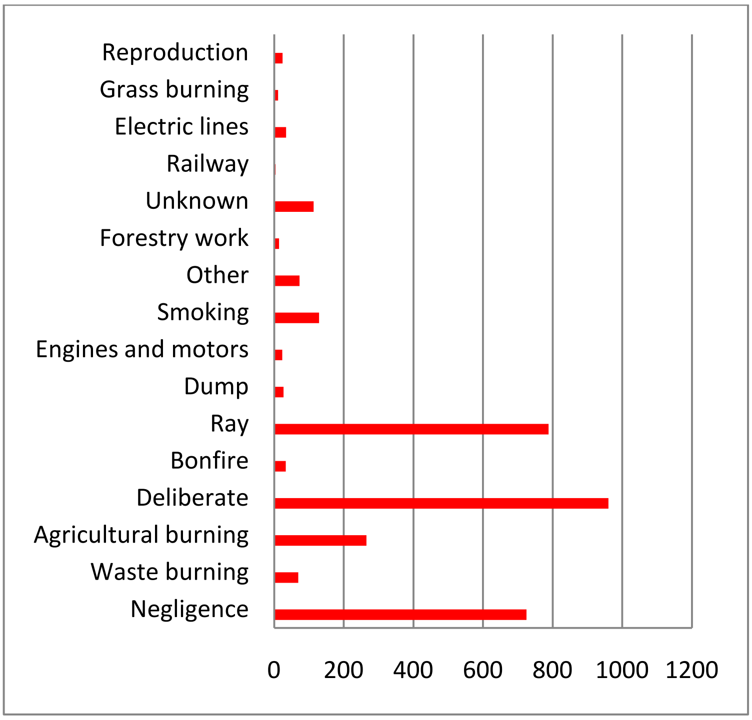

Figure 19: Causes of the fires in Valencian Community

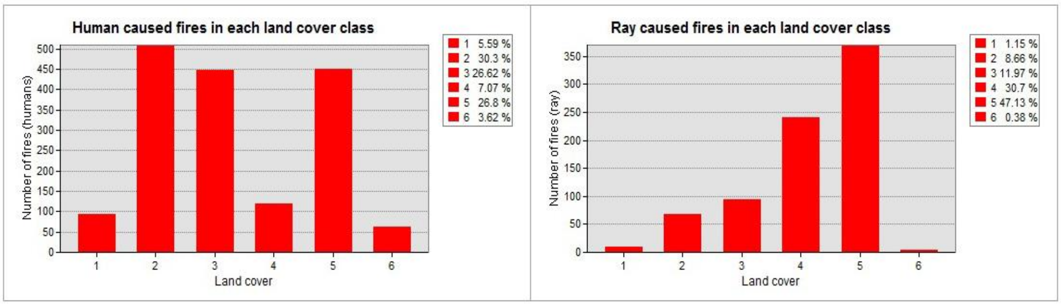

Figure 20: Occurrences of fires caused by human activities (left) and lightening (right) depicted in each land cover class

Appendix C: Visual results of interaction between fires and covariates

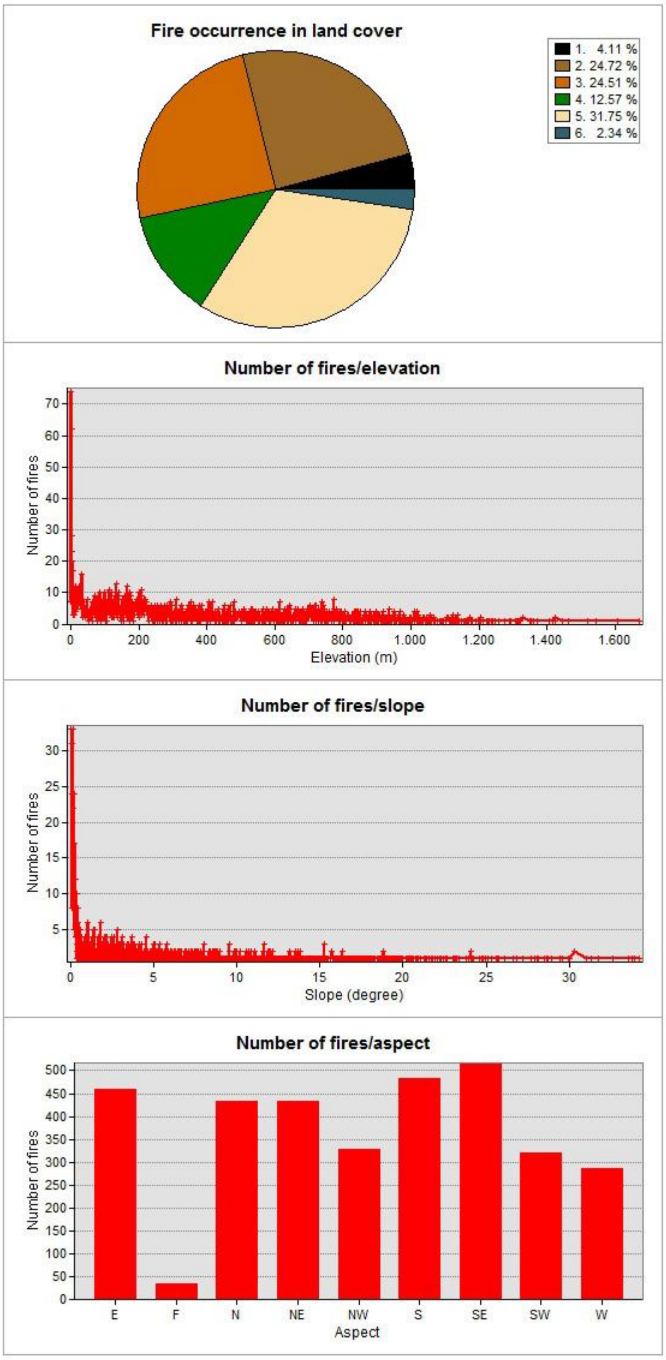

Figure 21: Fire characteristics in relation with land cover and topography covariates

Appendix D: Quadrat counting based on covariates and window (4x4)

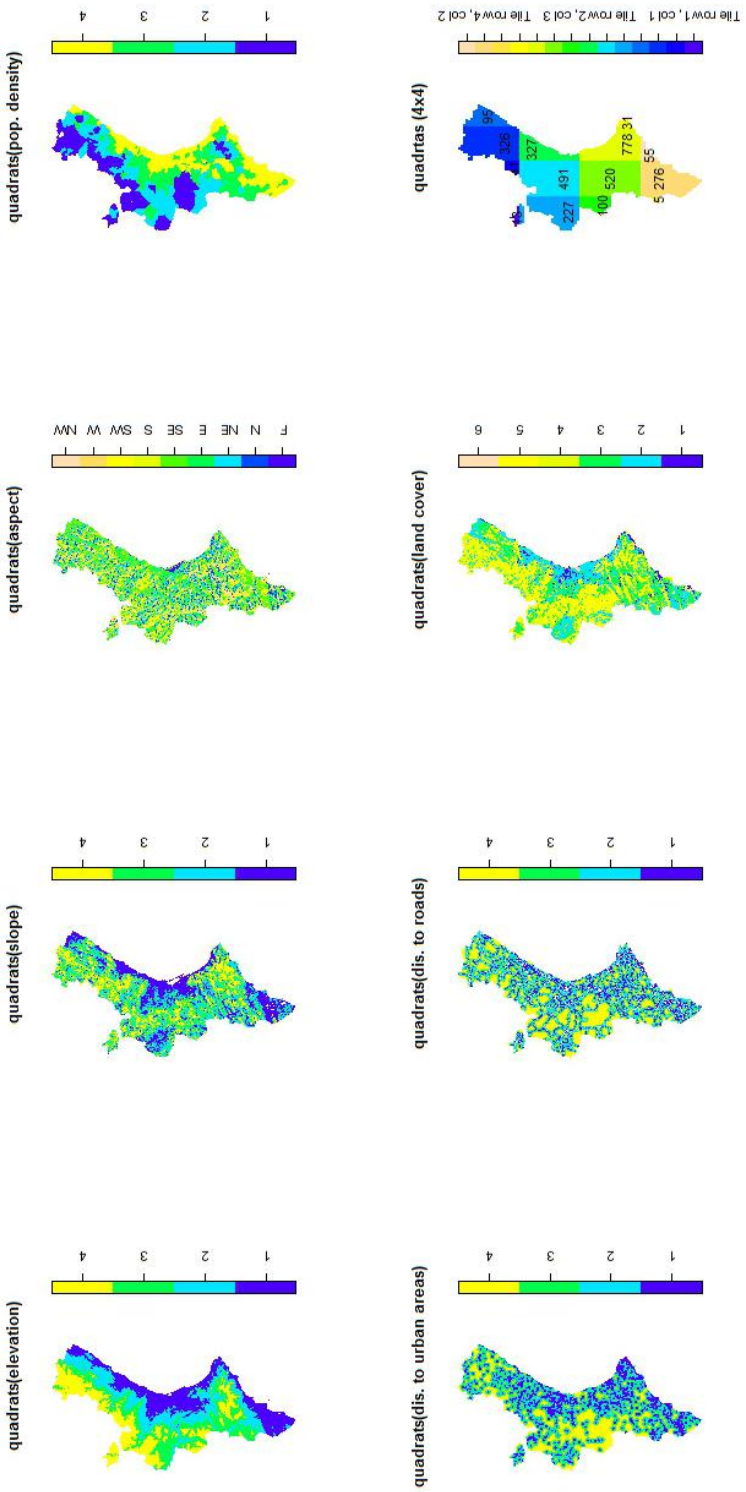

Figure 22: Quadrat counting based on covariates and regular squares (4x4)

Appendix E: R Code

```
---------------------------------------------------------------------
#author    Adriana Tanfara
#purpose   Spatial analysis and investigation of fire events
                  occurrences in the Valencian Community, Spain
#date      25 January 2011
---------------------------------------------------------------------
#required libraries
library(spatstat)
library(maptools)
library(rgdal)
library(sp)

#working directory
setwd("G:\\Thesis\\R\\R_data")

#read shapefile data source
valencia<-readShapePoly("CV.shp")

#Convert to window
valencia.w<-as(valencia, "owin")

#read points (fires)
fires<-read.csv("myFires.csv", h=T, sep=",", dec=".")

#define coordinate columns for fires
x<-fires$x
y<-fires$y

#creating point pattern
myFires<-ppp(x,y, window=valencia.w)

##inputting rasters (covaiates)

#elevation
e=readAsciiGrid(fname="elevation.asc")
el=as.im(e)

#slope
s=readAsciiGrid(fname="slope.asc")
sl=as.im(s)

#aspect
a=readAsciiGrid(fname="aspectrc.asc")
as=as.im(a)
as.fa=cut(as,breaks=9,label=c("F","N","NE","E","SE","S","SW","W","NW
"))

#distance to urban areas
disu=readAsciiGrid(fname="disturb.asc")
du=as.im(disu)

#distance to main roads
disr=readAsciiGrid(fname="distro.asc")
dr=as.im(disr)
```

```
#population density
popd=readAsciiGrid(fname="popdens.asc")
pd=as.im(popd)

#land cover
landco=readAsciiGrid(fname="lc.asc")
lc.fa=as.im(landco)

#ploting covariates
par(mfrow=c(2,4))
image(el, main="Elevation (m)")
image(sl, main="Slope (degree)")
image(as.fa, main="Aspect")
image(pd, main="Population density (p/km^2)")
image(du, main="Dist to urban areas (m)")
image(dr, main="Dist to roads (m)")
image(lc.fa, main="Land cover")
plot(myFires,main="Fire data distribution",cex=0.2)

##Intensity
#Intensity under CSR
lamb=summary(myFires)$intensity
lamb

#quadrat count (4x4)
q=quadratcount(myFires,nx=4,ny=4)
q

#quadrats determined by elevation
SPe=quantile(el)
elC=cut(el,breaks=SPe,labels=1:4)
Tel=tess(image=elC)
qel=quadratcount(myFires,tess=Tel)
qel

#quadrats determined by slope
SPs=quantile(sl)
slC=cut(sl,breaks=SPs,labels=1:4)
Tsl=tess(image=slC)
qsl=quadratcount(myFires,tess=Tsl)
qsl

#quadrats determined by aspect
Tas=tess(image=as.fa,breaks=9)
qas=quadratcount(myFires,tess=Tas)
qas

#quadrats determined by population density
SPpd=quantile(pd)
pdC=cut(pd,breaks=SPpd,labels=1:4)
Tpd=tess(image=pdC)
qpd=quadratcount(myFires,tess=Tpd)
qpd

#quadrats determined by distance to urban areas
SPdu=quantile(du)
duC=cut(du,breaks=SPdu,labels=1:4)
Tdu=tess(image=duC)
```

```
qdu=quadratcount(myFires,tess=Tdu)
qdu

#quadrats determined by distance to roads
SPdr=quantile(dr)
drC=cut(dr,breaks=SPdr,labels=1:4)
Tdr=tess(image=drC)
qdr=quadratcount(myFires,tess=Tdr)
qdr

#quadrats determined by land cover
Tlc=tess(image=lc.fa,breaks=6)
qlc=quadratcount(myFires,tess=Tlc)
qlc

#Goodness of fit for quadrat counting
quadrat.test(myFires,nx=4,ny=4)
quadrat.test(myFires,tess=Tel)
quadrat.test(myFires,tess=Tsl)
quadrat.test(myFires,tess=Tas)
quadrat.test(myFires,tess=Tpd)
quadrat.test(myFires,tess=Tdu)
quadrat.test(myFires,tess=Tdr)
quadrat.test(myFires,tess=Tlc)

#pltting generated quadrats
par(mfrow=c(2,4))
plot(Tel,main="quadrats(elevation)")
plot(Tsl,main="quadrats(slope)")
plot(Tas,main="quadrats(aspect)")
plot(Tpd,main="quadrats(pop. density)")
plot(Tdu,main="quadrats(dis. to urban areas)")
plot(Tdr,main="quadrats(dis. to roads)")
plot(Tlc,main="quadrats(land cover)")
plot(q,main="quadrtas (4x4)")

#Plot intensity map
plot(density(myFires),main="Fire intensity map\nValencian
Community")

#Plot density surface
persp(density(myFires),phi=20,theta=-50,main="Density function
surface\nValencian Community")

##Distance methods
#generating envelopes
EF=envelope(myFires,Fest,nsim=19)
EG=envelope(myFires,Gest,nsim=19)
KG=envelope(myFires,Kest,nsim=19)

#ploting EDF
par(mfrow=c(1,2))
plot(EF,main="Empty space distances")
plot(EG,main="Nearest neighbour distances")
plot(EK,main="Pairwise distances")

##fitting the model
#comb1
fit1=ppm(myFires,~el,covariates=list(el=el))
```

```
fit2=ppm(myFires,~sl,covariates=list(sl=sl))
fit3=ppm(myFires,~factor(as),covariates=list(as=as.fa))
fit4=ppm(myFires,~pd,covariates=list(pd=pd))
fit5=ppm(myFires,~du,covariates=list(du=du))
fit6=ppm(myFires,~dr,covariates=list(dr=dr))
fit7=ppm(myFires,~factor(lc),covariates=list(lc=lc.fa))
#comb2
fit8=ppm(myFires,~el+sl,covariates=list(el=el,sl=sl))
fit9=ppm(myFires,~el+factor(as),covariates=list(el=el,as=as.fa))
fit10=ppm(myFires,~el+du,covariates=list(el=el,du=du))
fit11=ppm(myFires,~el+dr,covariates=list(el=el,dr=dr))
fit12=ppm(myFires,~el+pd,covariates=list(el=el,pd=pd))
fit13=ppm(myFires,~el+factor(lc),covariates=list(el=el,lc=lc.fa))
fit14=ppm(myFires,~sl+factor(as),covariates=list(sl=sl,as=as.fa))
fit15=ppm(myFires,~sl+du,covariates=list(sl=sl,du=du))
fit16=ppm(myFires,~sl+dr,covariates=list(sl=sl,dr=dr))
fit17=ppm(myFires,~sl+pd,covariates=list(sl=sl,pd=pd))
fit18=ppm(myFires,~sl+factor(lc),covariates=list(sl=sl,lc=lc.fa))
fit19=ppm(myFires,~factor(as)+du,covariates=list(as=as.fa,du=du))
fit20=ppm(myFires,~factor(as)+dr,covariates=list(as=as.fa,dr=dr))
fit21=ppm(myFires,~factor(as)+pd,covariates=list(as=as.fa,pd=pd))
fit22=ppm(myFires,~factor(as)+factor(lc),covariates=list(as=as.fa,lc
=lc.fa))
fit23=ppm(myFires,~du+dr,covariates=list(du=du,dr=dr))
fit24=ppm(myFires,~du+pd,covariates=list(du=du,pd=pd))
fit25=ppm(myFires,~du+factor(lc),covariates=list(du=du,lc=lc.fa))
fit26=ppm(myFires,~dr+pd,covariates=list(dr=dr,pd=pd))
fit27=ppm(myFires,~dr+factor(lc),covariates=list(dr=dr,lc=lc.fa))
fit28=ppm(myFires,~pd+factor(lc),covariates=list(pd=pd,lc=lc.fa))
#comb3
fit29=ppm(myFires,~el+sl+factor(as),covariates=list(el=el,sl=sl,as=a
s.fa))
fit30=ppm(myFires,~el+sl+du,covariates=list(el=el,sl=sl,du=du))
fit31=ppm(myFires,~el+sl+dr,covariates=list(el=el,sl=sl,dr=dr))
fit32=ppm(myFires,~el+sl+pd,covariates=list(el=el,sl=sl,pd=pd))
fit33=ppm(myFires,~el+sl+factor(lc),covariates=list(el=el,sl=sl,lc=l
c.fa))
fit34=ppm(myFires,~el+factor(as)+du,covariates=list(el=el,as=as.fa,d
u=du))
fit35=ppm(myFires,~el+factor(as)+dr,covariates=list(el=el,as=as.fa,d
r=dr))
fit36=ppm(myFires,~el+factor(as)+pd,covariates=list(el=el,as=as.fa,p
d=pd))
fit37=ppm(myFires,~el+factor(as)+factor(lc),covariates=list(el=el,as
=as.fa,lc=lc.fa))
fit38=ppm(myFires,~el+du+dr,covariates=list(el=el,du=du,dr=dr))
fit39=ppm(myFires,~el+du+pd,covariates=list(el=el,du=du,pd=pd))
fit40=ppm(myFires,~el+du+factor(lc),covariates=list(el=el,du=du,lc=l
c.fa))
fit41=ppm(myFires,~el+dr+pd,covariates=list(el=el,dr=dr,pd=pd))
fit42=ppm(myFires,~el+dr+factor(lc),covariates=list(el=el,dr=dr,lc=l
c.fa))
fit43=ppm(myFires,~el+pd+factor(lc),covariates=list(el=el,pd=pd,lc=l
c.fa))
fit44=ppm(myFires,~sl+factor(as)+du,covariates=list(sl=sl,as=as.fa,d
u=du))
fit45=ppm(myFires,~sl+factor(as)+dr,covariates=list(sl=sl,as=as.fa,d
r=dr))
```

```
fit46=ppm(myFires,~sl+factor(as)+pd,covariates=list(sl=sl,as=as.fa,p
d=pd))
fit47=ppm(myFires,~sl+factor(as)+factor(lc),covariates=list(sl=sl,as
=as.fa,lc=lc.fa))
fit48=ppm(myFires,~sl+du+dr,covariates=list(sl=sl,du=du,dr=dr))
fit49=ppm(myFires,~sl+du+pd,covariates=list(sl=sl,du=du,pd=pd))
fit50=ppm(myFires,~sl+du+factor(lc),covariates=list(sl=sl,du=du,lc=l
c.fa))
fit51=ppm(myFires,~sl+dr+pd,covariates=list(sl=sl,dr=dr,pd=pd))
fit52=ppm(myFires,~sl+dr+factor(lc),covariates=list(sl=sl,dr=dr,lc=l
c.fa))
fit53=ppm(myFires,~sl+pd+factor(lc),covariates=list(sl=sl,pd=pd,lc=l
c.fa))
fit54=ppm(myFires,~factor(as)+du+dr,covariates=list(as=as.fa,du=du,d
r=dr))
fit55=ppm(myFires,~factor(as)+du+pd,covariates=list(as=as.fa,du=du,p
d=pd))
fit56=ppm(myFires,~factor(as)+du+factor(lc),covariates=list(as=as.fa
,du=du,lc=lc.fa))
fit57=ppm(myFires,~factor(as)+dr+pd,covariates=list(as=as.fa,dr=dr,p
d=pd))
fit58=ppm(myFires,~factor(as)+dr+factor(lc),covariates=list(as=as.fa
,dr=dr,lc=lc.fa))
fit59=ppm(myFires,~factor(as)+pd+factor(lc),covariates=list(as=as.fa
,pd=pd,lc=lc.fa))
fit60=ppm(myFires,~du+dr+pd,covariates=list(du=du,dr=dr,pd=pd))
fit61=ppm(myFires,~du+dr+factor(lc),covariates=list(du=du,dr=dr,lc=l
c.fa))
fit62=ppm(myFires,~du+pd+factor(lc),covariates=list(du=du,pd=pd,lc=l
c.fa))
fit63=ppm(myFires,~dr+pd+factor(lc),covariates=list(dr=dr,pd=pd,lc=l
c.fa))
#comb4
fit64=ppm(myFires,~el+sl+factor(as)+du,covariates=list(el=el,sl=sl,a
s=as.fa,du=du))
fit65=ppm(myFires,~el+sl+factor(as)+dr,covariates=list(el=el,sl=sl,a
s=as.fa,dr=dr))
fit66=ppm(myFires,~el+sl+factor(as)+pd,covariates=list(el=el,sl=sl,a
s=as.fa,pd=pd))
fit67=ppm(myFires,~el+sl+factor(as)+factor(lc),covariates=list(el=el
,sl=sl,as=as.fa,lc=lc.fa))
fit68=ppm(myFires,~el+sl+du+dr,covariates=list(el=el,sl=sl,du=du,dr=
dr))
fit69=ppm(myFires,~el+sl+du+pd,covariates=list(el=el,sl=sl,du=du,pd=
pd))
fit70=ppm(myFires,~el+sl+du+factor(lc),covariates=list(el=el,sl=sl,d
u=du,lc=lc.fa))
fit71=ppm(myFires,~el+sl+dr+pd,covariates=list(el=el,sl=sl,dr=dr,pd=
pd))
fit72=ppm(myFires,~el+sl+dr+factor(lc),covariates=list(el=el,sl=sl,d
r=dr,lc=lc.fa))
fit73=ppm(myFires,~el+sl+pd+factor(lc),covariates=list(el=el,sl=sl,p
d=pd,lc=lc.fa))
fit74=ppm(myFires,~el+factor(as)+du+dr,covariates=list(el=el,as=as.f
a,du=du,dr=dr))
fit75=ppm(myFires,~el+factor(as)+du+pd,covariates=list(el=el,as=as.f
a,du=du,pd=pd))
fit76=ppm(myFires,~el+factor(as)+du+factor(lc),covariates=list(el=el
,as=as.fa,du=du,lc=lc.fa))
```

```
fit77=ppm(myFires,~el+factor(as)+dr+pd,covariates=list(el=el,as=as.f
a,dr=dr,pd=pd))
fit78=ppm(myFires,~el+factor(as)+dr+factor(lc),covariates=list(el=el
,as=as.fa,dr=dr,lc=lc.fa))
fit79=ppm(myFires,~el+factor(as)+pd+factor(lc),covariates=list(el=el
,as=as.fa,pd=pd,lc=lc.fa))
fit80=ppm(myFires,~el+du+dr+pd,covariates=list(el=el,du=du,dr=dr,pd=
pd))
fit81=ppm(myFires,~el+du+dr+factor(lc),covariates=list(el=el,du=du,d
r=dr,lc=lc.fa))
fit82=ppm(myFires,~el+du+pd+factor(lc),covariates=list(el=el,du=du,p
d=pd,lc=lc.fa))
fit83=ppm(myFires,~el+dr+pd+factor(lc),covariates=list(el=el,dr=dr,p
d=pd,lc=lc.fa))
fit84=ppm(myFires,~sl+factor(as)+du+dr,covariates=list(sl=sl,as=as.f
a,du=du,dr=dr))
fit85=ppm(myFires,~sl+factor(as)+du+pd,covariates=list(sl=sl,as=as.f
a,du=du,pd=pd))
fit86=ppm(myFires,~sl+factor(as)+du+factor(lc),covariates=list(sl=sl
,as=as.fa,du=du,lc=lc.fa))
fit87=ppm(myFires,~sl+factor(as)+dr+pd,covariates=list(sl=sl,as=as.f
a,dr=dr,pd=pd))
fit88=ppm(myFires,~sl+factor(as)+dr+factor(lc),covariates=list(sl=sl
,as=as.fa,dr=dr,lc=lc.fa))
fit89=ppm(myFires,~sl+factor(as)+pd+factor(lc),covariates=list(sl=sl
,as=as.fa,pd=pd,lc=lc.fa))
fit90=ppm(myFires,~sl+du+dr+pd,covariates=list(sl=sl,du=du,dr=dr,pd=
pd))
fit91=ppm(myFires,~sl+du+dr+factor(lc),covariates=list(sl=sl,du=du,d
r=dr,lc=lc.fa))
fit92=ppm(myFires,~sl+du+pd+factor(lc),covariates=list(sl=sl,du=du,p
d=pd,lc=lc.fa))
fit93=ppm(myFires,~sl+dr+pd+factor(lc),covariates=list(sl=sl,dr=dr,p
d=pd,lc=lc.fa))
fit94=ppm(myFires,~factor(as)+du+dr+pd,covariates=list(as=as.fa,du=d
u,dr=dr,pd=pd))
fit95=ppm(myFires,~factor(as)+du+dr+factor(lc),covariates=list(as=as
.fa,du=du,dr=dr,lc=lc.fa))
fit96=ppm(myFires,~factor(as)+du+pd+factor(lc),covariates=list(as=as
.fa,du=du,pd=pd,lc=lc.fa))
fit97=ppm(myFires,~factor(as)+dr+pd+factor(lc),covariates=list(as=as
.fa,dr=dr,pd=pd,lc=lc.fa))
fit98=ppm(myFires,~du+dr+pd+factor(lc),covariates=list(du=du,dr=dr,p
d=pd,lc=lc.fa))
#comb5
fit99=ppm(myFires,~el+sl+factor(as)+du+dr,covariates=list(el=el,sl=s
l,as=as.fa,du=du,dr=dr))
fit100=ppm(myFires,~el+sl+factor(as)+du+pd,covariates=list(el=el,sl=
sl,as=as.fa,du=du,pd=pd))
fit101=ppm(myFires,~el+sl+factor(as)+du+factor(lc),covariates=list(e
l=el,sl=sl,as=as.fa,du=du,lc=lc.fa))
fit102=ppm(myFires,~el+sl+factor(as)+dr+pd,covariates=list(el=el,sl=
sl,as=as.fa,dr=dr,pd=pd))
fit103=ppm(myFires,~el+sl+factor(as)+dr+factor(lc),covariates=list(e
l=el,sl=sl,as=as.fa,dr=dr,lc=lc.fa))
fit104=ppm(myFires,~el+sl+factor(as)+pd+factor(lc),covariates=list(e
l=el,sl=sl,as=as.fa,pd=pd,lc=lc.fa))
fit105=ppm(myFires,~el+sl+du+dr+pd,covariates=list(el=el,sl=sl,du=du
,dr=dr,pd=pd))
```

```
fit106=ppm(myFires,~el+sl+du+dr+factor(lc),covariates=list(el=el,sl=
sl,du=du,dr=dr,lc=lc.fa))
fit107=ppm(myFires,~el+sl+du+pd+factor(lc),covariates=list(el=el,sl=
sl,du=du,pd=pd,lc=lc.fa))
fit108=ppm(myFires,~el+sl+dr+pd+factor(lc),covariates=list(el=el,sl=
sl,dr=dr,pd=pd,lc=lc.fa))
fit109=ppm(myFires,~el+factor(as)+du+dr+pd,covariates=list(el=el,as=
as.fa,du=du,dr=dr,pd=pd))
fit110=ppm(myFires,~el+factor(as)+du+dr+factor(lc),covariates=list(e
l=el,as=as.fa,du=du,dr=dr,lc=lc.fa))
fit111=ppm(myFires,~el+factor(as)+du+pd+factor(lc),covariates=list(e
l=el,as=as.fa,du=du,pd=pd,lc=lc.fa))
fit112=ppm(myFires,~el+factor(as)+dr+pd+factor(lc),covariates=list(e
l=el,as=as.fa,dr=dr,pd=pd,lc=lc.fa))
fit113=ppm(myFires,~el+du+dr+pd+factor(lc),covariates=list(el=el,du=
du,dr=dr,pd=pd,lc=lc.fa))
fit114=ppm(myFires,~sl+factor(as)+du+dr+pd,covariates=list(sl=sl,as=
as.fa,du=du,dr=dr,pd=pd))
fit115=ppm(myFires,~sl+factor(as)+du+dr+factor(lc),covariates=list(s
l=sl,as=as.fa,du=du,dr=dr,lc=lc.fa))
fit116=ppm(myFires,~sl+factor(as)+du+pd+factor(lc),covariates=list(s
l=sl,as=as.fa,du=du,pd=pd,lc=lc.fa))
fit117=ppm(myFires,~sl+factor(as)+dr+pd+factor(lc),covariates=list(s
l=sl,as=as.fa,dr=dr,pd=pd,lc=lc.fa))
fit118=ppm(myFires,~sl+du+dr+pd+factor(lc),covariates=list(sl=sl,du=
du,dr=dr,pd=pd,lc=lc.fa))
fit119=ppm(myFires,~factor(as)+du+dr+pd+factor(lc),covariates=list(a
s=as.fa,du=du,dr=dr,pd=pd,lc=lc.fa))
#comb6
fit120=ppm(myFires,~el+sl+factor(as)+du+dr+pd,covariates=list(el=el,
sl=sl,as=as.fa,du=du,dr=dr,pd=pd))
fit121=ppm(myFires,~el+sl+factor(as)+du+dr+factor(lc),covariates=lis
t(el=el,sl=sl,as=as.fa,du=du,dr=dr,lc=lc.fa))
fit122=ppm(myFires,~el+sl+factor(as)+du+pd+factor(lc),covariates=lis
t(el=el,sl=sl,as=as.fa,du=du,pd=pd,lc=lc.fa))
fit123=ppm(myFires,~el+sl+factor(as)+dr+pd+factor(lc),covariates=lis
t(el=el,sl=sl,as=as.fa,dr=dr,pd=pd,lc=lc.fa))
fit124=ppm(myFires,~el+sl+du+dr+pd+factor(lc),covariates=list(el=el,
sl=sl,du=du,dr=dr,pd=pd,lc=lc.fa))
fit125=ppm(myFires,~el+factor(as)+du+dr+pd+factor(lc),covariates=lis
t(el=el,as=as.fa,du=du,dr=dr,pd=pd,lc=lc.fa))
fit126=ppm(myFires,~sl+factor(as)+du+dr+pd+factor(lc),covariates=lis
t(sl=sl,as=as.fa,du=du,dr=dr,pd=pd,lc=lc.fa))
#comb7#
fit127=ppm(myFires,~el+sl+factor(as)+du+dr+pd+factor(lc),covariates=
list(el=el,sl=sl,as=as.fa,du=du,dr=dr,pd=pd,lc=lc.fa))

#AIC for model selection (calculated for 127 models)
AIC(fitt127)

#Goodness of fitted model (formal)
test=envelope(fit127,Kinhom,lambda=lambda,nsim=50,control=list(expan
d=1))
plot(test,main="test50")

#Validation using residuals
par(mfrow=c(2,3))
lurking(fit127, expression(el), type="pearson", xlab="Elevation
(m)")
```

```
lurking(fit127, expression(sl), type="pearson", xlab="Slope
(degree)")
lurking(fit127, expression(pd), type="pearson", xlab="Population
density (p/km^2)")
lurking(fit127, expression(du), type="pearson", xlab="Dist. to urban
areas (m)")
lurking(fit127, expression(dr), type="pearson", xlab="Dist. to main
roads (m)")
diagnose.ppm(fit127,type="pearson")
```