Estimation of Risk Factors of Human Ignition of Fires in Spain by Means of Logistic Regression[1]

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Abstract
Human activity is the main factor of forest fires ignitions in Spain, as in all countries of southern Europe. As most of fires are the result of human activity and behavior, their analysis must be based on the signs left in the territory by those who are held responsible. But since this is normally difficult to achieve directly, a good solution could be inferring human sources of ignition from indirect indicators of its number, activity and distribution. The first objective of this work was to identify significant variables than can be used to predict the human ignition risk in Spain. The second one is to propose a human caused fire occurrence prediction model, with a long-term scope. The model is constructed using logistic regression by exploring relationships between the density of human caused fires in the municipality forest area during a period of 13 years (dependent variable) and 26 geographical, socio-economical and environmental variables (independent ones) for 7704 municipalities of the Spanish peninsular territory and Baleares Islands. The model predicts properly the probability that each spatial unit have of high or low incidence of man-caused fires and provides an idea of the relative importance of each human factor in the explaining ignition.

Introduction

According to data published by the General Board for Nature Conservation (GBNC) for the period 1988-99, 96 % of the fires in Spain were due, either directly or indirectly, to human intervention, which indicates the close link between fires and human activities. In view of these figures, it is obviously interesting to include the human factor in prevention plans. Nevertheless this evidence contrasts with the scant importance attributed to human, as opposed to physical, factors in quantitative analysis of fire risk.

Human risk of ignition may be defined as the probability of a fire occurring as a result of the presence and activity, either directly or indirectly, of human activity. The evaluation of human activity as an agent of ignition is a complex task, one reason being the lack of data in respect of the number of people present in a forest zone, and another being their activities and their use of fire (Vega García et al 1993). In fact,

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the temporal and daily data needed to evaluate the human factor in fire risk is not generally available (Martell and others 1987) in contrast to variables such as temperature or relative humidity. Moreover, man is one of the most dynamic elements of space and his activity or attitudes on certain occasions does not tend to follow specific spatial patterns, or rather these are more difficult to determine, as in the case of pyromania or specific deliberate motivation. However, for other causes, such as those relating to recreational activities or agricultural burning it would seem easier to obtain spatial variables. All these difficulties have frequently led to investigators and the responsible fire-fighting bodies to adopt two solutions in this respect; either leave the human risk factor out of their prediction models or at least deal with it only very marginally, or they obtain some indirect estimators of human risk activity, namely indicators of activities which are the usual cause of fire and which are generally structural in nature, i.e. they refer to the most permanent feature of the land and population.

This study is based on the hypothesis that fires caused by man in a reiterated manner in a specific geographical sector cannot be explained by physical or natural conditions alone. Nor can the cause be reduced to factors of random individual human behavior. We consider that this type of fire is usually the result of a social norm and that we need to look for its cause in the conditions of the forest land, and the environmental, social and economic conditions of each area.

Studies have been carried out since the nineteen sixties in respect of the human risk of ignition in an attempt to consider the human factor by way of explanation or to predict the occurrence of fire using more or less indirect variables for the number, distribution and activities of human beings on the land, obtained mainly from censuses and survey sources (Altobellis 1983, Bertrand and Baird 1975, Christiansen and Folkman 1971, Cole and Kaufman 1963, Doolittle1972, Hasbrough 1961, Johnson 1968, Jones et al 1965). In general these studies tend to conclude that the activities perpetrated are more important than the incendiaries themselves.

In the nineteen eighties the first studies of fire risk began to appear, clearly focused more on spatial or cartographic aspects, which considered together with physical variables and human variables (Aerial Information Systems Inc. 1981, Bradshaw et al 1987, Chuvieco and Congalton 1989, Donoghue and Main, 1985, Phillips and Nickey 1978). The number of such studies increased in the nineteen-nineties due to the greater availability of digital cartographic and statistical information incorporated in Geographical Information Systems (among others: Abhineet et al 1996, Benvenuti et al 2002, Chou 1990 and 1992; Chuvieco et al 1999, Kalabokidis et al 2002, Salas and Chuvieco 1994, Vega-García et al 1993 and 1995, Vasconcelos yet al 2001, Vliegher 1992). All these studies basically use variables relating to recreational activities in the forest areas, means of communication (proximity to roads and paths etc) or to anthropic presence and pressure (population density, human settlements). These are the variables used from the outset in almost all the research since they are the easiest to spatialise, although depending on zone, they are not always the most important. Sometimes certain modifications are introduced or different means are proposed to estimate a specific factor, (for example, using the distance to the most populated zones instead of roads, or using the accessibility of certain recreational elements instead of camping zones)or new elements are introduced which have not been previously considered, such as the commercial value of the forest or they type of property.

Despite the existence of these empirical works, there is still a long way to go in terms of prediction and modeling of fire risk of human origin. An initial step in the right direction would be to identify and establish the relative importance of all the risk factors linked to human activity in each study zone. This previous effort is lacking in some of the research reviewed, which in addition might even seem somewhat reductionist, since some studies only consider a small part of the overall human factors which in reality would be linked to the occurrence. However, it is positive to note that there is a developing interest in the use of this type of variable.

Objectives

The aim of this study is to present a method and provisional results obtained for modeling human risk on a national scale in Spain. We attempted to obtain an index by means of logistic regression to predict the probability of a spatial unit having high or low occurrence of fires caused by human activity. In turn the intention was for the model to provide an idea of the relative importance of each human factor in the occurrence of fires. The results are represented as risk maps.

Study area and unit of analysis

Since the objective is to obtain an overall view of the human ignition factors in Spain, the study area covers the whole Spanish peninsula and the Balearic Islands. The regions of Navarra and the Canary Islands could not be included due to a lack of significant variables. In future works, the diverse causes and risk situations throughout the country will be taken into account, comparing different models for various regions.

The spatial unit of analysis was chosen in function of the dependent variable, i.e. bearing in mind the availability of data regarding fires. In Spain for example, the ignition points cannot be considered, as the parts of fires where the coordinates x and y can be assembled are very scarce. The townships (7004 in the study zone) were used as a base, both for geographically locating fires using parts supplied by the DGCN and for generating independent variables.

Methodology

The first step in our study was to identify, through bibliographic sources and by consulting experts, the anthropic factors relating to the occurrence of forest fires in Spain (Martínez et al 2004). We were then able to draw up a list of risk factors in which one or several variables are proposed for quantitative measurement. Depending on the data source, these variables were either statistical and/or cartographic.

Generating risk and spatial analysis variables

The “geo database” created for the 7004 municipalities in the study area comprises 23 variables of historic occurrence and causality of forest fires, and 108 independent variables relating to social, demographic and territorial characteristics. The statistical variables were compiled from censuses, and spatial variables such as the road network, protected natural spaces, land use etc. were obtained from digital maps provided by national bodies. In order to obtain municipal surfaces and other types of derived variables it was necessary to make varied spatial analyses using GIS tools:

the following programmes were used: ArcInfo 7.2, ArcGis-ArcInfo 8, ArcView 3.2. e Idrisi 3.2.

Dependent Variable

One of the most relevant questions was the choice of dependent variable, which we would attempt to explain and predict, and which was finally defined as the number of fires caused by human intervention occurring between 1988 and 2000. There are two reasons for the selection of this time period: the availability of data and the greater homogeneity of that data both in terms of compilation of the information and the nature of the causes of fires occurring in this period. Due to the variety of size of the municipality, which was the spatial unity of reference chosen for the analysis, it was necessary to normalize the variable by dividing the number of fires per municipality by the municipal forested area, according to what the GBNC considers to be the ignition index.

Independent Variables

One of the main difficulties of this work was to find digital data in an accessible format which was up to date and homogeneous for all the municipalities in the country. Frequently the data necessary to measure a specific factor does not exist for all or any of the study units. On other occasions the economic or compilation effort was extremely high. Therefore it was not possible to obtain an "ideal" number of variables, and several variables were discarded which, theoretically, were closely related to fires (for example recreational areas, hunting , suppression and prevention resources, agricultural burning permits, electrical lines, waste dumps, forest paths etc.). Altogether 108 independent variables were generated, grouped according to the type of human risk factor to which they contributed. Although many of them in reality represent similar concepts, an attempt was made to ensure that each variable would have some specific characteristic which would differentiate it from the rest. Nevertheless, as long as we work with a group of variables the degree of multiple co-linearity is inevitably very high. Despite this fact, the aim was to select solely those variables which due to a specific factor had a greater influence on or relation to the occurrence of fires which we did not know at the start.

In order to reduce the possible effects of multiple co-linearity and the noise of irrelevant variables, exploratory analyses and correlation matrices were made between all the variables. Moreover, various statistics of the diagnosis of multiple co-linearity obtained in linear regression analysis were examined, such as the tolerance coefficient, the variance inflaction factor (VIF), etc. Subsequent to these analyses 26 variables were selected to create the final risk model.

In order to ascertain that these 26 variables were adequate, several comparative statistical tests were carried out on the data groups. We wished to verify whether or not there was a significant difference in the values of the variables corresponding to the two municipal samples, some with a high and others with a low incidence of fire. If these test showed a scant difference between the values of a specific variable in these two groups of municipalities it could be assumed that this variable was not related to the occurrence of fires. U-Mann-Whitney and Ji Cuadrado's parametric and non-parametric proofs were applied to two samples and H de Kruskal-Wallis' for four samples. The three proofs showed very similar results, significantly indicating all the pre-selected variables at a level of less than 0,05.

Logistic Regression

A logistic regression model has been used previously and with good results to predict the probability of fires and to examine the most critical factors of incidence both on a local (Chou 1992, Chou et al 1993, Latham and Schilieter 1989, Loftsgaarden and Andrews 1992, Vasconcelos et al 2000, Vega-García *et al* 1993 and 1995) and on regional and global scale (Chuvieco *et al* 1999, Martell et al 1987 y 1989). This regression technique which is flexible and easy to use is the most well known and frequently used method when the dependent variable to be predicted is dichotomous according to the values of a group of predictor variables. It is based on the following function:

$$f(z) = \frac{1}{1+e^{-z}}$$

where z is obtained by an estimated linear combination of independent variables by means of maximum probability adjustment. The z values may be interpreted as the probability of occurrence of the phenomenon. converts the values for z into a continuous function with a rank oscillating between 0 and 1. Values less than 0,5 are usually assigned to non-occurrence of the phenomenon and those which are equal or greater are interpreted as occurrence. $f(z)$

Before making the regression analysis, only the municipalities which fulfilled two requirements were chosen: those which had one or more fires during the study period and those which comprised more than 50 ha (0,5 km^2) of forest surface. This was an effort to reduce cases with extreme or unusual values in the dependent variable. Thus the number of cases was reduced from 7,704 to 6,080 municipalities. In addition, in order to validate the results obtained, 60% of the cases were selected at random (that is, 3619 municipalities) which were finally used to calculate the regression function. The remaining 40% were subsequently used to validate or measure the quality of the estimations.

On the other hand, as it was a question of predicting the high or low probability of fires, the dependent variable needed to be converted to a dichotomous variable. In order to do so it was decided to order the 3,619 municipalities selected from lesser to greater incidence taking as reference the dependent variable. The variable was then divided into three groups with an identical number of cases (1206). The municipalities in the first group (low incidence) were given the value 0 and those of the third group (high incidence) were assigned the value of 1. The municipalities in the second group (average incidence) were not taken into account in construction of the model.

Calculations of logistic regression were made with the statistical packet SPSS v.11.5. S Various automatic methods were tested controlling the criteria for which the variables were introduced and eliminated from the equation**:** by one step forward, one step back and by introducing all. The cut off point for classifying the cases was established at 0.5.

Results

Having tried various automatic methods of variable selection the "stepwise forward selection algorithm" was finally chosen, which provided 17 different models. Among these the final model was chosen which achieved the highest overall result and included the greatest number of variables. Although perhaps it is not advisable to include such a high number of variables in the model, we chose this method in an attempt, rather than obtain good predictions, to achieve an explanatory model in which it would be possible to observe the most influential variables and factors in the occurrence. The variables included in the model (with Arabic numerals) and grouped by factor type (indicated in italics) and are as follows:

Social and economic transformations in urban areas: anthropic pressure on forest areas and urban growth:

1. Percentage of urban forest interface zone in the municipality (IUFSUP_P)

2. De facto population variation between 1950 and 1970 (CRE50_70)

Social and economic transformations in rural areas: rural exodus, population ageing, abandonment of woodland cultivation and traditional activities.

3. Percentage of agricultural area which became forest land between the nineteen-seventies and nineties. (ICO_90)

Maintenance of traditional activities linked to fire in rural areas: agriculture and stock keeping

4. Occupied percentage in the primary sector (OCUPAGRA)

5. Percentage of cultivated forest land interface in the municipality (ICFSUP_P)

6. Livestock density in extensive regime on the forest surface area (GAN_FOR)

7. Percentage of woodland pasture interface in the municipality (IPFSUP_P)

Disinterest in forest land and its conservation. Insufficient protection and management of forest land:

8. Percentage of forest surface with less management, control and planning over time (private forest land, land belonging to local authorities with free use, consortiums and neighboring forest common land). (NOGES_PF)

Accessibility and risk deriving from communication roads

9. Density of roads per municipal surface area (ROADMU_D)

10. Density of railway lines per municipal surface area (FFCCMU_D)

Other factors which might cause fires through accidents or negligence:

11. Density of agricultural machinery on the municipal surface area (MAQUIN_D)

12. Percentage of the interface zone between risk infrastructures (waste dumps mines and quarries) and forest areas (IFIFSU_P)

Structure of the landscape, land and population:

13. Density and agricultural plots (agricultural fragmentation) (PAR_SEXP)

14. Percentage of population living in disseminated sites (DISEM_P)

15. Density of singular population entities (ENTSIN_M)

16. Municipal average of fragmentation index. (FRAG7X7)

Factors which generate conflicts and which could lead to deliberate fires

17. Unemployment rate (PARO)

Table 1 shows the regression coefficients and the *Wald* statistic, with its corresponding level of significance for each independent variable. Variables have been arranged in descending order according to the *Wald* statistic. The change was also calculated in –2LL if a variable is eliminated at each step (-2LL is the Napieran logarithm of the coefficient verisimilitude multiplied by –2), which is also a complementary measure of the importance of variables in the model. The variables which appear first in *table 1*, in descending order, are those which have had the most influence on the outbreak of fires at a national level: The density of agricultural machinery, density of agricultural plots, the density of singular population entities, density of livestock in extensive regimes in forest areas and the unemployment rate.

Table 1— *Variables included in the model and regression coefficients*

Variables: Step 17	Coef B	E.T.	Wald	gl	Sig.	Exp(B)	Change in -2LL if the variable is eliminated
MAQUIN_D	0,538	0,047	129,150	1	0,0000	1,7132	186,234
PAR_SEXP	0,013	0,002	64,595	1	0,0000	1,0130	76,107
ENTSIN_M	6,999	0,974	51,647	1	0,0000	1095,8907	71,469
GAN_FOR	0,013	0,002	51,451	1	0,0000	1,0127	88,979
PARO	0,026	0,005	25,014	1	0,0000	1,0259	25,047
ICFSUP_P	-0,130	0,027	22,853	1	0,0000	0,8778	23,785
CRE50_70	0,011	0,002	22,796	1	0,0000	1,0109	27,955
ROADMU_D	0,002	0,000	16,492	1	0,0000	1,0020	17,040
FRAG7X7	102,114	25,165	16,465	1	0,0000	2,225E+44	16,895
DISEM_P	-0,027	0,007	15,474	1	0,0001	0,9731	17,271
FFCCMU_D	0,003	0,001	9,377	1	0,0022	1,0030	9,624
OCUPAGRA	0,010	0,004	7,391	1	0,0066	1,0101	7,431
IPFSUP_P	-0,125	0,046	7,282	1	0,0070	0,8827	7,549
IFIFSU_P	0,767	0,317	5,840	1	0,0157	2,1531	7,609
IUFSUP_P	0,319	0,141	5,100	1	0,0239	1,3752	6,490
ICO_90	0,011	0,005	4,759	1	0,0291	1,0109	4,667
NOGES_PF	-0,005	0,002	4,443	1	0,0350	0,9949	4,420
Constant	-3,766	0,326	133,579	1	0,0000	0,0231	

According to these results, risk factors such as land structure, specially fragmentation of agricultural activity and the negligent use of fire in traditional activities in rural areas (burning brush carried out by shepherds to regenerate pasture and burning slash and the remains of pruning and thinning) are of considerable importance in the outbreak of fires in Spain. Other variables included in the model are: the urban-forest interface, presence of road and railway density and the population variation between 1950-1970. Most of the coefficient signs for each variable are logical with respect to prior knowledge of the causes of fires in Spain.

For some variables the relation is not expected, as in the case of the agricultural forest interface which has a negative coefficient. These contradictory signs may be due to possible effects of multiple co-linearity which it was not possible to eliminate.

The goodness of fit of the regression is indicated in *table 2*. The percentage of overall success of classification is over 85 % and reaches 90% for municipalities with a low incidence of fire. It may be said that the accuracy of the classification is very good if we consider that the study area is quite large and covers extremely varied situations of human risk and causality and the fact that physical variables were not taken into account.

Table 2— *Contingency table of success/error of the classification by logistic regression. Predicted cases opposed to observed cases(sample of 60%)*

OBSERVED	**PREDICTED**			
	Lowa	Alta	% de acuerdo	
	0	1		
Low occurrence	0	1080	117	90,23
High occurrence	1	221	976	81,54
Global percentage of success	**85,88**			

In order to confirm the validity of the results, the equation resulting from the model was applied to the control sample which included 40 % of the municipalities (1640). The global percentage in agreement is almost the same (84% correctly classified) as that obtained with the original sample of 60% with which the model was constructed.

Figure 1 shows a map contrasting the probability of fire predicted with that observed for the group of municipalities used in the validation (sample of 40%). The municipalities where prediction and occurrence do not coincide are represented in blue (overestimated or predicted but not observed) or in green (observed but not predicted or underestimated). In these cases the model does not function adequately, which indicates that it would be necessary to take into account other explanatory variables or even to design another different model for these cases. The correctly classified models are indicated in red and orange.

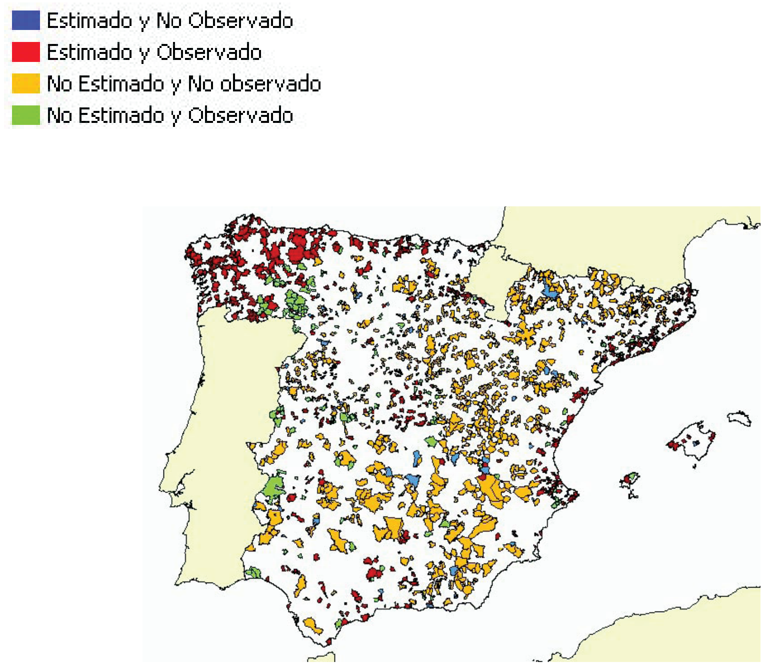

Figure 1—Validation of the model of estimation of outbreak . Predicted outbreak as opposed to observed outbreak (sample of 40%)

Once the validity of the model had been observed, it was applied to all the cases in the study area which fulfilled the previously mentioned requirements (6080 municipalities) and a map was generated expressing on a probability scale of 0 to 1, the estimated possibility that a municipality would have a high incidence of fires caused by human activity (*fig. 2*). The scale has been divided into five intervals with the same number of cases (quantile) to facilitate visualization. The municipalities in white are those which were not considered in the analysis since they had not suffered any fires and did not have over 50 hectares of forest land.

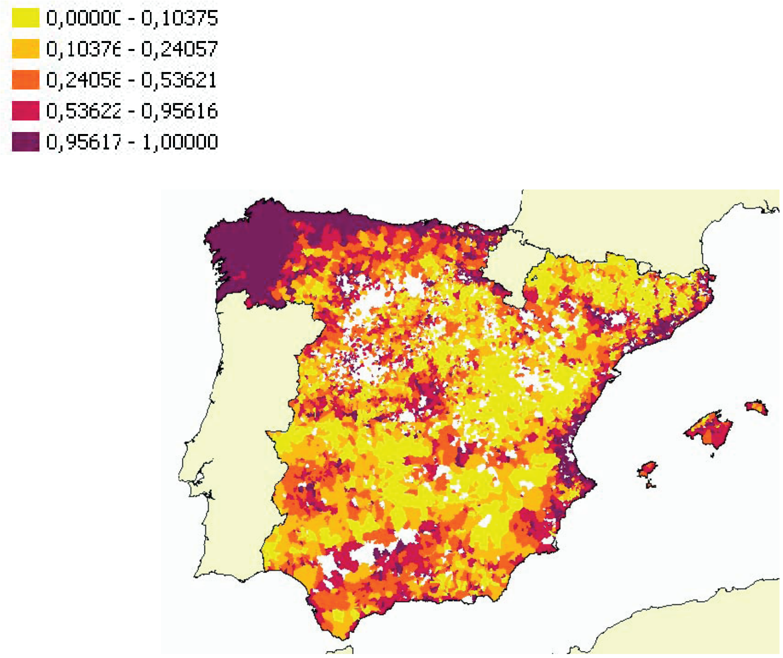

Figure 2—Probability of high incidence of fires due to human factors

A visual comparison of this map and the map featured in *figure 3*, which represents the original dependent variable provides an idea of the appropriateness of the model to the reality of historical incidence.

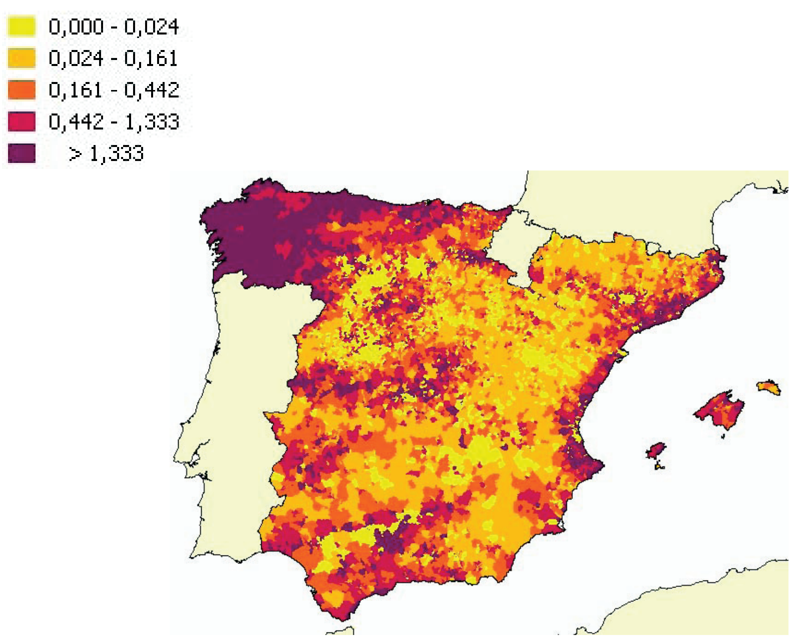

Figure 3— Ignition index: number of forest fires caused by human intervention /forest surface area of the municipality (classification of intervals by quantile)

Conclusions

This paper has attempted to show the potential of spatial statistics and cartography of structural risk as tools for improving knowledge of forest fires, particularly necessary with a view to planning and designing prevention plans and policies at a national level. The method of logistic regression has once more shown that although there are some limitations, it is a simple and efficient technique for studying the variables which explain fire risk, in this case to identify the most influential human factors on a global scale in Spain.

The results obtained confirm the importance of the negligent or intentional use of fire in agricultural activities in rural areas. According to the data on causes for the period 1988-2001, burning of underbrush to regenerate pasture and agricultural fires for various purposes are the main recognized cause of both negligence(42,7%) and deliberate fires (69,6%). Both presuppose 20,4% of the total causes of fires, although it is estimated that they may reach 50%. On the other hand, factors referring to the structure of the landscape or territory such as the division of agricultural plots (smallholdings) or the rate of fragmentation linked to the abandonment of agricultural land (percentage of agricultural to forest land) would seem to contribute to the creation of extremely hazardous situations. We consider that the generalized abandonment of agricultural plots, however small in size, which have been colonized by highly inflammable vegetation constitutes a serious threat to the neighboring forest, despite the latter being well tended. This situation is sometimes aggravated by the existence of social conflict and exploitation of the area.

The results also confirm that the proximity of certain types of occupation may contribute to the outbreak of fire (forest/agricultural, forest/pasture and urban/forest interfaces) since in addition to the risk associated with negligent or deliberate use of fire in rural or urban activities, these structures imply a greater transit through forest zones as opposed to large homogeneous forest masses. Specifically, risk may be very high in the urban forest interface zone. Other influential factors are the form in which the population inhabits and is distributed throughout the territory (density of singular entities of population and population living in disseminated areas) since this may encourage a greater presence of human agents in habitual contact with the forest area.

Finally as expected, the presence and density of roads and railways shows a significant link with fires, as well as the variation of population between 1950 and 1970, an period which was notable in Spain for its rural exodus and urban growth. In addition the unemployment rate appears to be quite related to the occurrence. In this sense some authors (Bertrand y Baird 1975, Leone y Vita 1982, Vélez 2000), have indicated that economic difficulties may influence the appearance of conflicts manifested in the use of intentional fire.

All these results should be considered only as valid for Spain, since there is no guarantee that they might be applicable in any other place. It is highly likely that some of the variables selected here are not linked to the occurrence of fire in other regions or countries. Also the model developed is global in nature, in the sense that it does not take into account local and regional variations within the study area, which of course are quite important. We therefore consider that this work should be extended to construct regression models weighted especially for each of the units of analysis by means of spatial statistical technique of a local type which would enable us to identify the variables with regression coefficients, which vary significantly throughout the area both in sign and magnitude (Fotheringham 2002).

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