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Wildfire risk mapping: considering environmental change in space and time

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Abstract

Geographic Information Systems (GIS) have been used to model and assess wildfire risk in Mediterranean environments at a local landscape scale. Here, two GIS models are presented; one previously proposed (Salas and Chuvieco 1994), and one extended upon this incorporating an index of patch contiguity to consider the spatial configuration of the landscape. Both models suggest that wildfire risk has increased in the study area, SPA 56 'Encinares del río Alberche y Cofio' (central Spain), driven largely by processes associated with agricultural abandonment. However, results suggest that the extended model is better suited to highlight changes in the spatial structure of the landscape (i.e. increased homogeneity). Both models are used to examine potential changes in future wildfire risk via a logistic regression model that predicts future land cover from observed changes. Results suggest wildfire risk will continue to rise across the landscape in the future. Methodologies such as the one presented here could be used in other landscapes to quickly assess wildfire risk and its change due to environmental change.

Introduction

Fire is an ever-present risk in the semi-arid environments of the Mediterranean Basin. During 1994, 17,156 fires in Spain, burnt over 405,000 hectares of forest, woodland and grazing land, damaged farm and holiday buildings, and caused the deaths of 22 people (Velez 1995). Although an extreme year, this example illustrates the importance of understanding the risk that wildfire hazard imposes for both management and mitigation purposes. In this sense, a 'hazard' is a potential threat to humans or their interests and 'risk' is the likelihood of hazard occurrence (Smith 1992). As with many other natural hazards, understanding how wildfire risk will change in the future under changing environmental conditions will allow this risk to be more effectively managed.

Wildfires, and the subsequent patterns of vegetation regeneration that in turn influence future wildfire activity, typify the feedbacks between ecological pattern and process emphasised by landscape ecologists (Turner 1989). When humans are present in a landscape, as they are ubiquitously in the Mediterranean Basin, they become part of this pattern-process feedback; human patterns of land-use influence where wildfires occur and how they spread. In turn, the footprints of these fires influence patterns of vegetation and its regeneration, which in turn influences human land-use, and so on. Attempts to assess the risk of wildfire burning one particular point in a landscape must, therefore, be spatial in nature. For example, the evaluation of the wildfire risk presented in a particular area demands the consideration of both the factors involved in the potential ignition of a fire in that area and the factors influencing the possibility of fire spreading into it from an adjacent area. These factors include the vegetation (fuel) available to burn, topography, human activities, and climatic conditions of both the area concerned and the landscape(s) surrounding it. Any changes in these environmental conditions are likely to lead to a change in wildfire risk.

This paper uses a Geographic Information System (GIS) to examine how wildfire risk has changed in a region (described in more detail below) west of the city of Madrid, Spain. Potential future changes in risk, in response to possible future changes in land-cover due to agricultural abandonment, are modelled. Building upon previous wildfire risk mapping research, a consideration of how spatial changes in vegetation structure in the region is incorporated, and changes in the spatial pattern of risk are examined. First, previous wildfire risk mapping studies using GIS are reviewed and the potential changes in landscape composition and configuration, and the impacts of these for wildfire risk, are examined for the study area. Next, the methods used to spatially model wildfire risk and future potential changes in land-cover are presented. The results from this modelling are then presented and analysed, focussing on the spatial aspects of wildfire risk, before the results are placed into the wider context of wildfire risk assessment in the Mediterranean.

Mediterranean Wildfire Risk Assessment using GIS

Many wildfire risk mapping studies have used GIS to integrate several layers of spatial, wildfire-related data to derive maps of risk for their study areas (e.g. Chuvieco and Congalton 1989, Chuvieco and Salas 1996, Castro and Chuvieco 1998, Camia et al. 1999, Chuvieco et al. 1999). Table 1 presents examples of the types of data that have been used in such studies in the Mediterranean. This approach has been the most frequent use of GIS in wildfire modelling studies (Perry 1998), and stems from the utility of GIS to represent, analyse, and manipulate spatial data. Further, these studies have predominantly used a qualitative-objective method, using variables concerning the condition of vegetation (fuel) available to burn and the presence of human activity. This method assesses risk by assigning specific values to combinations of risk-related variables according to their (perceived) importance (Chuvieco et al. 1999).

Forestry managers in the Mediterranean frequently use this type of approach to assess wildfire risk on a daily or weekly basis. However, it seems that there has been no use of this type of wildfire risk modelling for forecasting how risk may change further into the future under different environmental conditions in this region. For example, changes in land cover due to changes in land use, particularly agricultural change and abandonment often cited as occurring in the Mediterranean Basin (e.g. MacDonald et al. 2000), and climatic changes, will alter the environmental conditions influencing wildfire risk. Using GIS-based wildfire risk modelling techniques and projecting into the future for different environmental conditions is one way we might quickly and conveniently assess how risk will change.

Table 1. Data used in previous GIS wildfire risk studies. All studies of this nature in the Mediterranean have included human activity because of the high number of human-caused fires in this region.

	Chuvieco and Congalton (1989)	Salas and Chuvieco (1994)	Chuvieco and Salas (1996)	Castro and Chuvieco (1998)
Data Resolution (m)	50	50	30	50
Vegetation (Fuel)	yes	yes	yes	yes
Elevation	yes	yes	no	no
Aspect	yes	yes	yes	yes
Slope Angle	yes	no	yes	yes
Temperature	no	no	yes	yes
Air Humidity	no	no	yes	no
Human Activity	yes	yes	yes	yes

Langran (1992) suggested that the treatment of time would make GIS ‘complete’ and that without it GIS would remain a tool of “ad-hoc problem solving and demonstration projects” (Langran 1992, p.4). Further, Perry (1998) noted that the lack of temporality in contemporary GIS had until then prevented the explicit simulation of wildfire events within them, and in particular prevented adequate representation of the complexities of wildfire spread. In the time since there has been little advance in the capabilities of GIS to represent time or spatial change dynamically, although the topic has been increasingly discussed in the area (e.g. see the special edition of *Cartography and Geographic Information Systems*, ‘Dealing with Time’; 1999, vol. 26, no. 2). GIS is currently used for inherently static assessments (“snapshots”) of underlying processes when compared to dynamic, process-based wildfire models (e.g. Mouillot et al. 2001, also see examples in Keane et al. 2004). Thus, while this snapshot nature may be adequate for assessing wildfire *ignition* risk, which actually only occurs at one instant in time, it is rather inadequate for assessing the wildfire’s subsequent *behaviour* and spread. Substituting space for time may help to overcome this inadequacy. By considering the spatial structure of landscape vegetation (a wildfire’s fuel) improved representation of wildfire risk due to the behavioural aspects of the hazard might be achieved. Here, I incorporate a spatial index of contiguity into a previous GIS wildfire risk model to attempt to do this.

Recently there has been much debate concerning the effects that changes in current ecological disturbance regimes (notably wildfire and agricultural disturbance) might have on landscape heterogeneity in the Mediterranean. For example, Perez et al. (2003) found that increased fire occurrence, resulting from increases in fire risk due to abandonment, reduces heterogeneity by merging smaller patches into larger burned areas. Theoretically, this homogenisation of land cover will further promote disturbances that spread (e.g. wildfire, see Turner et al. 1989, Turner and Dale 1991) leading to the occurrence of larger fires. However, Lloret et al. (2002) found that for their study area in north-east Spain, fires were more likely to occur in large homogenous areas of woodland and acted to actually increase heterogeneity (although it did not outweigh the homogeneity caused by agricultural abandonment and corresponding coalescence of natural vegetation patches). These previous studies in the Mediterranean Basin are in general agreement that agricultural abandonment and corresponding increases in wildfire risk (and occurrence) has led to increased landscape homogeneity. With this in mind, incorporating some measure of spatial heterogeneity into a wildfire risk model should not only improve representation of the behavioural processes, but is also necessary for more accurate projection of future risk.

Methods

Study Area

This study is focussed on the EU Special Protection Area number 56, ‘Encinares del río Alberche y Cofio’ (SPA 56), in central Spain (Figure 1). SPA 56 covers approximately 830 km^2 and is located 40 km to the southwest of the city of Madrid, within the Autonomous Community of Madrid. Lying on the southern slopes of the Sierra de Guadarrama

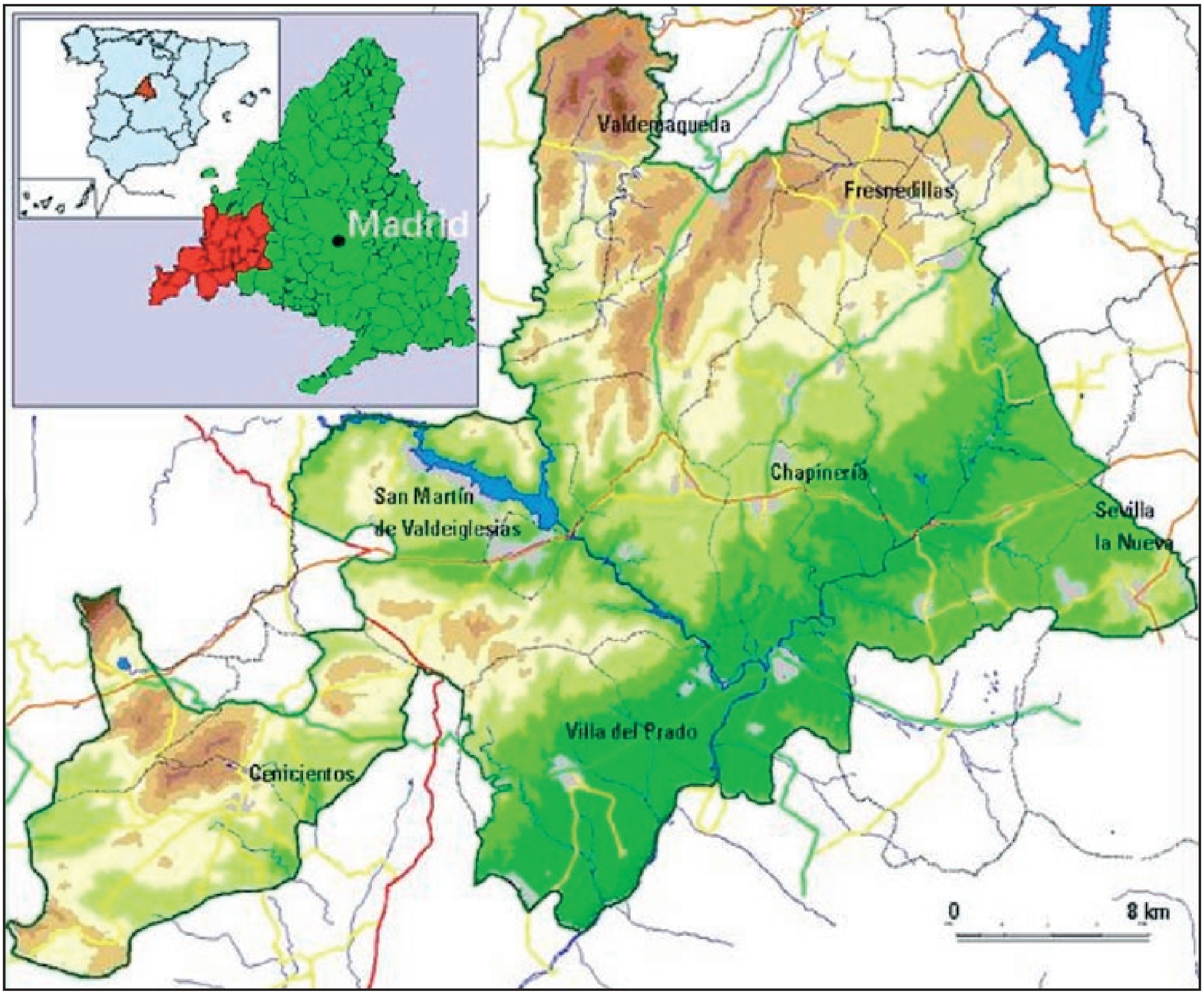

Figure 1. Study Area: SPA 56, 'Encinares del río Alberche y Cofio'. SPA 56 covers approximately 830 km^2 and is located 40 km to the southwest of the city of Madrid on the southern slopes of the Sierra de Guadarrama and Sierra de Gredos.

and Sierra de Gredos, altitudes range from 600 m ASL in the southeast to 1300 m in the northwest. SPA 56 contains a diverse range of habitats and environments including deciduous woodlands, pine forests, holm oak (*Quercus ilex*) woodland, *dehesa*, meadows, grasslands, scrubland, rocky outcrops and crags, riparian habitats and others besides. Land use in the landscape is of a highly multifunctional nature, with areas of pasture, grazing, residential and human recreation often juxtaposed or occurring simultaneously. SPA 56 thus contains and exhibits many of the features and characteristics found widely across the Mediterranean Basin (e.g. Grove and Rackham 2001).

Wildfire Risk Model Construction

The wildfire risk models examined here are based on the model presented by Salas and Chuvieco (1994). These authors constructed a wildfire risk model using a GIS for a study area located in the same region as SPA 56 (140km west of the city of Madrid) with a comparable altitudinal range (400 – 2,000m ASL), a very slightly cooler and wetter climate (a mean annual temperature range of 8° – 14°C and a mean rainfall range of 500 – 1500 mm versus 10° – 16°C and 400 – 800mm in SPA 56), and with similar vegetation (both landscapes dominated by *Quercus, Pinus* and *Cistus* species). A model using the same methods as Salas and Chuvieco (1994), both in terms of the types of data and variable weightings (see below), was used to create wildfire risk maps. Here, I also extend this model to consider the spatial configuration of land cover (as described below) and the model incorporating this spatial measure is compared to the method of Salas and Chuvieco (1994) for SPA 56. These wildfire risk assessment models are applied to both observed and predicted land cover maps with all other variables (elevation, location of roads/trails etc.) assumed to remain constant through time. Thus, although changes in other variables may occur, changes in wildfire risk through time are assessed with reference to changing vegetation conditions only.

As this study is based in large part on the model of Salas and Chuvieco (1994), the data chosen for inclusion in the wildfire risk models here were the same:

1. Land cover (vegetation)
2. DEM-derived data (aspect, illumination, elevation, slope)
3. Locations of firebreaks
4. Locations of roads and trails

Much of these data have been described previously by Romero-Calcerrada (2000) and Romero-Calcerrada and Perry (2004). Land cover data for 1984, 1991 and 1999 were derived from Landsat TM imagery and classified into 11 classes as shown in Figure 2 and Table 2. Romero-Calcerrada and Perry (2004) examined land cover changes occurring in SPA 56 between these years. Using landscape pattern metrics and transition matrices they found the configuration of land covers to be static through time, but that increasing rates of land cover change, possibly attributable to land abandonment (i.e. changes from pasture to scrubland), were evident in the landscape. They suggest that these changes might increase the flammability of the landscape as a whole (in turn leading to increased burned area, fire frequency and intensity); this contention is examined here in terms of wildfire risk.

Each variable is assigned a relative score and weight, according to its perceived influence on fire ignition and subsequent spread. Ignition Risk (IR, Equation 1) and Behaviour Risk (BR1 and BR2, Equations 2 and 3 respectively) maps were created from:

$$IR = 4H + 3V + 2I - E \quad (1)$$
$$BR1 = 5V + 4S + 3A - E - FB \quad (2)$$
$$BR2 = 5VC + 4S + 3A - E - FB \quad (3)$$

where:
- A = Aspect
- C = contiguity index
- E = Elevation
- FB = fire break
- H = human presence (i.e. within 30m of a road/trails)
- I = Illumination
- S = Slope
- V = vegetation

Vegetation flammability and fuel model scores (from the vegetation maps used here) were derived with reference to the system used by Salas and Chuvieco (1994, Table II). The vegetation (fuel) layer is generally considered one of the most important in wildfire risk modelling (Chuvieco and Congalton 1989, Keane et al. 2001, Viegas et al. 2001), with many fuel maps and classifications constructed to classify vegetation according to its propensity to burn (e.g. Dimitrakopoulos and Mateeva 1998, Nunez-Regueira et al. 2000, Dimitrakopoulos and Panov 2001, Sandberg et al. 2001). Vegetation is deemed the primary factor in determining the BR here, influencing fire intensity and thus propensity to spread. Vegetation is second only to human presence (proximity to roads/trails) for IR, and weighted accordingly.

The presence of humans is deemed most important regarding IR. Salas and Chuvieco (1994) claim clear evidence for human influence is shown in their analysis of Spanish fire reports between 1968 and 1988. This shows that most fires

Table 2. Vegetation classes and scores. The vegetation classes and risk scores used were derived from the method used by Salas and Chuvieco (1994). High scores indicate a greater relative contribution to wildfire risk compared to lower values. For example, Pine is perceived to be the land cover at greatest risk of burning and Water/Quarry, Urban and Burnt at least risk of burning.

Vegetation	Ignition Risk Score	Behaviour Risk Score
Pine	20	20
Mixed Forest (Pine and Oak)	16	18
Scrubland	16	18
Holm Oak	14	15
Holm Oak with Pasture	10	12
Deciduous Trees	10	12
Cropland	7	10
Pasture	5	5
Water/Quarry/Urban/Burnt	0	0

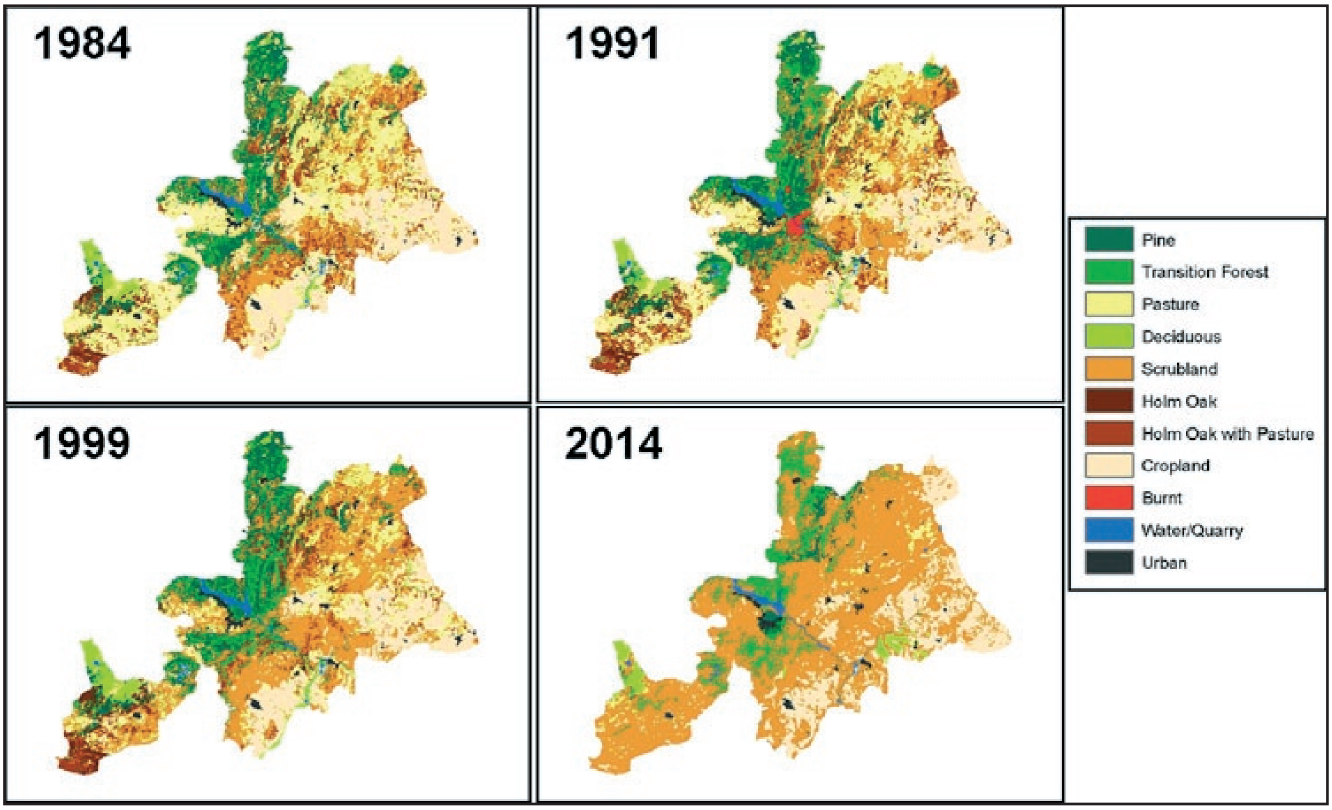

Figure 2. Land cover maps for 1984, 1991, 1999 and 2014 (predicted). Increases in scrubland commensurate with decreases in pasture land are observed for 1984-1999. The increases in flammability and homogenisation of the landscape associated with these land cover changes are likely to increase wildfire risk.

were started at weekends and during summer holidays, and near roads and trails. The summer holidays are the hottest and driest time of the year, with vegetation at its driest and most people using the landscape for recreation, and thus would expect to experience most fires. Similar analyses by Chuvieco and Salas (1996) and Vazquez and Moreno (1998) also found that most fires were started near roads and trails, although both used shorter-term data sets. Therefore in the model here, roads/trails, and areas within 30m, possess greater IR than the rest of the landscape. A similar buffer around road/trails to represent IR due to human activity has also been used in other studies (Chuvieco and Congalton 1989, Chuvieco and Salas 1996, Castro and Chuvieco 1998).

The illumination layer is used to represent spatial differences in mean air temperature and soil moisture across the landscape. In this case, increased illumination indicates increased air temperatures and lower soil moisture. This in turn reduces vegetation moisture, increasing wildfire risk (e.g. see Nunez-Regueira et al. 2000). The aspect layer is incorporated because of its influence on wind conditions, notably air moisture (Salas and Chuvieco 1994). Elevation and fire breaks were included in the BR assessment, acting to inhibit wildfire spread. All scores for these layers are as in Salas and Chuvieco (1994).

As outlined above, incorporating the spatial landscape structure in a GIS model of wildfire risk seems important to better represent the behavioural aspects of wildfire risk for both current and future landscapes. A spatially disaggregated index is required to represent landscape structure. At the patch-level the contiguity index is a measure of the spatial connectedness of cells and is calculated (using 'Fragstats', McGarigal and Marks 1995) as:

$$contiguity = \frac{\left[\frac{\sum_{r=1}^{a_i} c_{ir}}{a_i}\right] - 1}{v - 1} \tag{4}$$

where:

c_{ir} = contiguity value for pixel r in patch i

v = sum of the contiguity values in a 3-by-3 cell template

a_i = area of patch i (number of pixels)

The index is calculated for each patch in the landscape, and the value applied to each pixel comprising that patch. Thus, large, contiguous patches have larger contiguity index values. In the context of wildfire risk, a pixel with a larger contiguity index will thus be at greater risk of being burned as fire will spread more easily through the patch into it. This model incorporating contiguity into the model of Salas and Chuvieco (1994), will be referred to as CONMOD (CONtiguity MODel), and the model not including it as SACMOD (Salas And Chuvieco MODel). Contiguity is incorporated as a multiplier to the vegetation score in CONMOD (see Equation 3 above).

Final wildfire risk values for the two models are found by the combination of BR and IR maps:

$$\textit{SACMOD risk} = BR1 + IR \tag{5}$$

$$\textit{CONMOD risk} = BR2 + IR \tag{6}$$

Table 3. Classification of risk values. Final risk classes were derived as shown (source: Salas and Chuvieco 1994). For example, a pixel classed 'High' in BR and 'Medium' in IR has a final Wildfire Risk of 'High'. BR and IR values were classified using the following method; 'Low': risk value below 'Medium' range, 'Medium': risk values within one standard deviation greater or less than the mean risk value of the map (BR or IR), 'High': risk value within one standard deviation greater than the greatest 'Medium' risk value; 'Very High' all greater risk values.

	Behaviour Risk			
Ignition Risk	*Very High*	*High*	*Medium*	*Low*
Very High	Very High	Very High	Medium	Medium
High	Very High	High	Medium	Medium
Medium	High	High	Medium	Low
Low	Medium	Medium	Low	Low

Raw risk values derived from these equations may be scaled between 0 and 1 or classified directly into risk classes using the methodology as suggested by Salas and Chuvieco (1994, Table III); both methods are used here.

Logistic Regression Modelling of Land Cover Change

Logistic regression has frequently been used to statistically model land cover changes (e.g. Turner et al. 1996, Wear et al. 1998, Carmel et al. 2001). Logistic regression is particularly suited to modelling land cover change because of its suitability to predict a categorical (nominal) dependent variable from both continuous and categorical independent variables (e.g. see Hosmer and Lemeshow 1989), as was the nature of the independent data used here. The Multionomial Logit Model (MNLM, Equation 7) is used here as a probability model to estimate future land cover given a suite of 12 predictor variables (as shown in Table 4). The MNLM gives the probability of a pixel being in a state y_i from:

$$\Pr(y_i = m \mid x_i) = \frac{\exp(x_i \beta_m)}{1 + \sum_{j=2}^{J} \exp(x_i \beta_j)} \tag{7}$$

where:

x = predictor variable

m = land cover (e.g. cropland, scrubland)

J = total number of land cover types

β = estimated model parameter

To overcome the problems associated with spatial autocorrelation of data used in multiple regression analyses (see Lennon 2000), data was sampled at every tenth pixel in the x and y directions, as spatial autocorrelation was found to decrease monotonically above a lag of eight map pixels (~240m). Model coefficients were then estimated using the resulting 8,855 pixels for the land cover change observed between 1984 and 1999. These model coefficients where then used to predict land cover of the landscape in 2014, by applying the model coefficients to the data for 1999. The resulting map was smoothed using a Moore neighbourhood modal filter, as this had previously been found by the author to improve model accuracy (for models predicting observed land cover). The resulting predicted land cover map of the study area for the year 2014 is shown in Figure 2.

Table 4. Predictor variables used for multinomial logistic model. Units and resolution of measurement are shown. Values in brackets are years of measurement. See Romero-Calcerrada (2000) for details regarding 'Land Capability' measure.

Predictor Variable	Unit of Measurement	Resolution
Agricultural workers (1996)	Percentage of population	Municipality
Mean farmer age (1999)	Years	Municipality
Migration (1999)	Number of persons	Municipality
Population density (1999)	Persons/km^2	Municipality
Vegetation cover (1999)	Cover, see Figure 2	30m pixel
Aspect	Classified: N/NE/E/SE/S/SW/W/NW	30m pixel
Distance to a road	Metres	30m pixel
Distance to a water body	Metres	30m pixel
Distance to an urban area	Metres	30m pixel
Distance to edge of patch	Metres	30m pixel
Land capability	Ranked	30m pixel
Mean annual temperature	°C	30m pixel

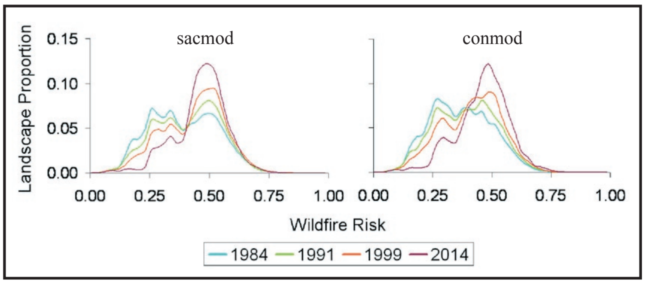

Figure 4. Wildfire risk distributions for SACMOD (left) and CONMOD (RIGHT) to year. Distributions for both models show risk increases and becomes less variable over time. Risk values are based on the raw, unclassified, risk values from equations 5 and 6.

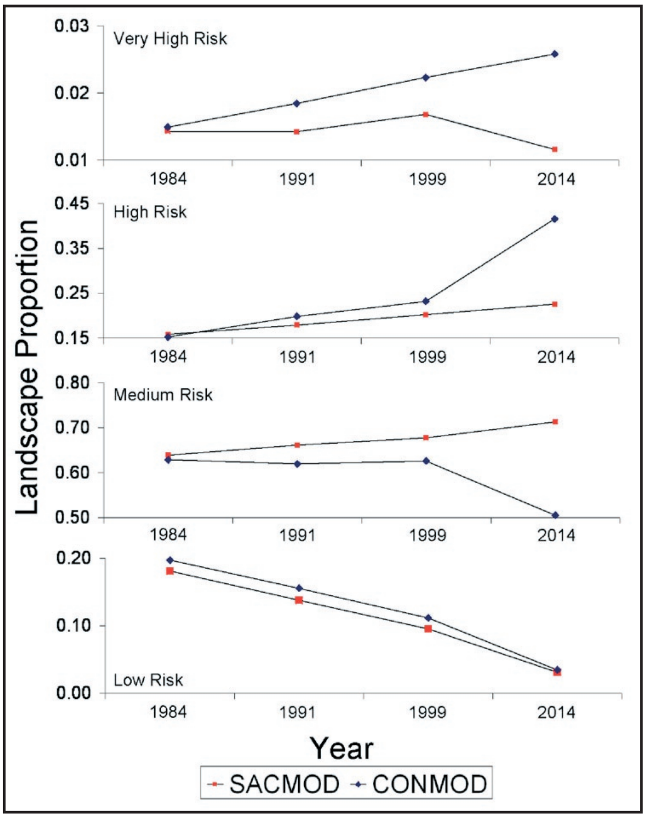

Figure 5. Wildfire risk class landscape proportions by year. SACMOD shows increasing landscape proportion in the 'Medium' and 'High' risk classes. CONMOD shows increasing landscape proportion in the 'High' and 'Very High' risk classes, but decreases in the 'Medium' risk class.

Model Results

Non-spatial Results

Both models suggest that mean wildfire risk has increased during the observed period (1984-1999) and will continue to increase into the future (see Figure 3). Further, risk is shown to become less variable through time (indicated by decreases in both standard deviation and the coefficient of variation, CV; see Figure 3). SACMOD suggests mean risk will increase by ~11% and ~18% for 1984-1999 and 1984-2014 respectively. CONMOD suggests mean risk will increase by ~12% and ~23% between the same periods. Thus, through time the proportion of risk values in the interval 0.4 – 0.6 increases, while the proportion of pixels at lower values decreases (see Figure 4).

SACMOD shows some increase in the 'Very High' class (~17%) in the observed period, but over the total period 1984-2014 the proportion of SPA 56 in this highest class will decrease by ~19% (Figure. 5). Examination of the SACMOD results shows that increases are found predominantly through the middle of the risk range ('Medium' and 'High' classes), and that pixels with 'Low' risk decrease in abundance for all time periods. In contrast, CONMOD shows marked (relative) increases in the 'Very High' and 'High' classes (~49% and ~53% respectively for 1984-1999 and ~73% and ~174% respectively for 1984-2014). No change was found in the proportion of the landscape defined as being at 'Medium' risk across the observed time period (-0.3% for 1984-1999) but a decrease of ~20% was predicted across the period 1984-2014. Thus, there is a marked difference between the two models for all observed and predicted time periods in each risk class except the 'Low' class. CONMOD indicates the proportion of the landscape at 'Medium' risk will remain largely constant (or decrease) but that the proportion of 'High' and 'Very High' will increase. Conversely, SACMOD indicates the proportion of the landscape at 'Very High' risk will remain largely constant (or decrease) but that the proportion of 'Medium' and 'High' risk will increase.

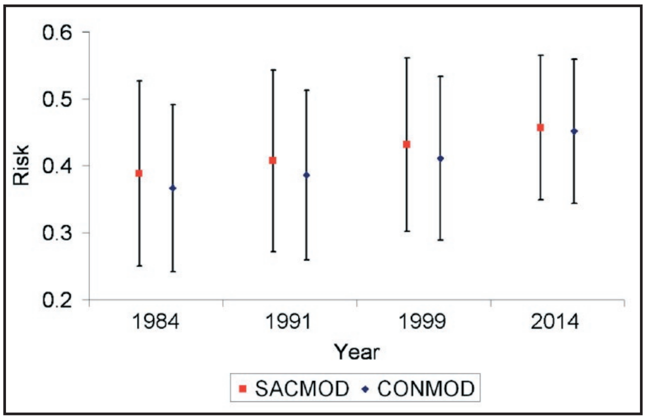

Figure 3. Mean risk for SACMOD and CONMOD by year. Mean wildfire risk increases and risk variability decreases with time. Error bars represent 1 S.D. Risk values are based on the raw, unclassified, risk values from equations 5 and 6.

Spatial Change

A suite of spatial indices (Table 5) were calculated at the landscape-level for the risk maps produced by the models (presented in Figures 6 and 7) using the software 'Fragstats' (McGarigal and Marks 1995). Of these indices, three (Contagion, Shannon's Diversity Index and Edge Density) can be used to illustrate three distinct differences (with spatial and non-spatial aspects) between risk maps produced by the models.

First, maps produced by CONMOD were relatively constant in their contagion values through time. In contrast SOCMOD shows increases through time. This difference is likely related to the increased proportions of 'High' and 'Low' risk pixels found in CONMOD compared with SACMOD. On inspecting the risk maps (Figures 6 and 7) we observe that the vast expanses of 'Medium' risk pixels found in SACMOD are more fragmented by patches of 'Low' or 'High' risk in the CONMOD maps. This difference may be attributed to the consideration of the spatial nature of wildfire risk in CONMOD via the contiguity index. Second, decreases in Shannon's Diversity Index (SDI) are observed in maps produced using SACMOD, but remain constant in maps produced using CONMOD. SDI is calculated by considering the relative proportions of the classes that make up a landscape. As described above, the results from SACMOD show an increasing dominance of the 'Medium' risk class through time (Figure 5) but CONMOD results indicate the proportion of 'Medium' risk pixels remains constant. Further, the four risk classes contribute much more evenly in the CONMOD map for 2014 (Figures 5 and 7). Thus, SDI decreases for SACMOD but remains relatively stable for CONMOD maps. Third, edge den-

Table 5. Spatial indices of wildfire risk maps. Differences are observed between the two model's output in their spatial configuration. CONMOD contagion values are constant through time, SOCMOD values increase; CONMOD Shannon's diversity index values are constant through time, SOCMOD values decrease; and CONMOD edge density values are greater than for SOCMOD.

	Number of Patches	Largest Patch Index	Edge Density	Mean Euclidean Nearest Neighbour	Contagion	Shannon's Diversity Index
SACMOD 1984	12,181	57.05	111.42	99.82	46.67	0.95
SACMOD 1991	11,917	62.80	105.39	101.87	48.71	0.91
SACMOD 1999	11,848	64.85	105.01	102.24	50.26	0.88
SACMOD 2014	9,337	69.35	82.57	112.42	59.16	0.73
CONMOD 1984	12,262	55.89	111.33	100.79	46.22	0.96
CONMOD 1991	12,272	57.09	112.29	102.23	45.24	0.98
CONMOD 1999	12,961	56.49	115.30	101.94	45.66	0.96
CONMOD 2014	11594	12.62	96.44	118.72	49.43	0.92

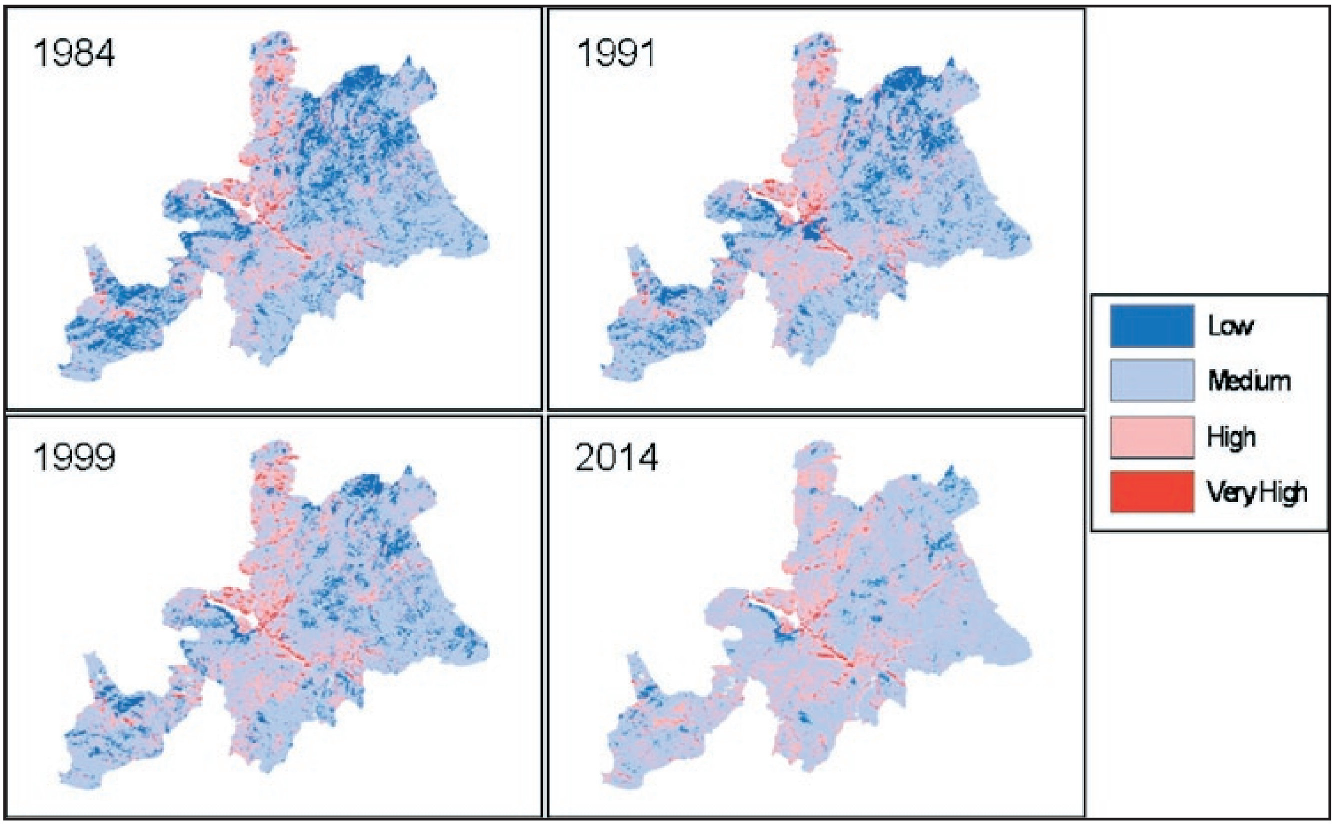

Figure 6. Wildfire risk maps produced by SACMOD. Through time the proportion 'Medium' risk increases, shown as the landscape becomes dominated by large homogenous light blue areas. Areas at greatest risk are shown in bright red.

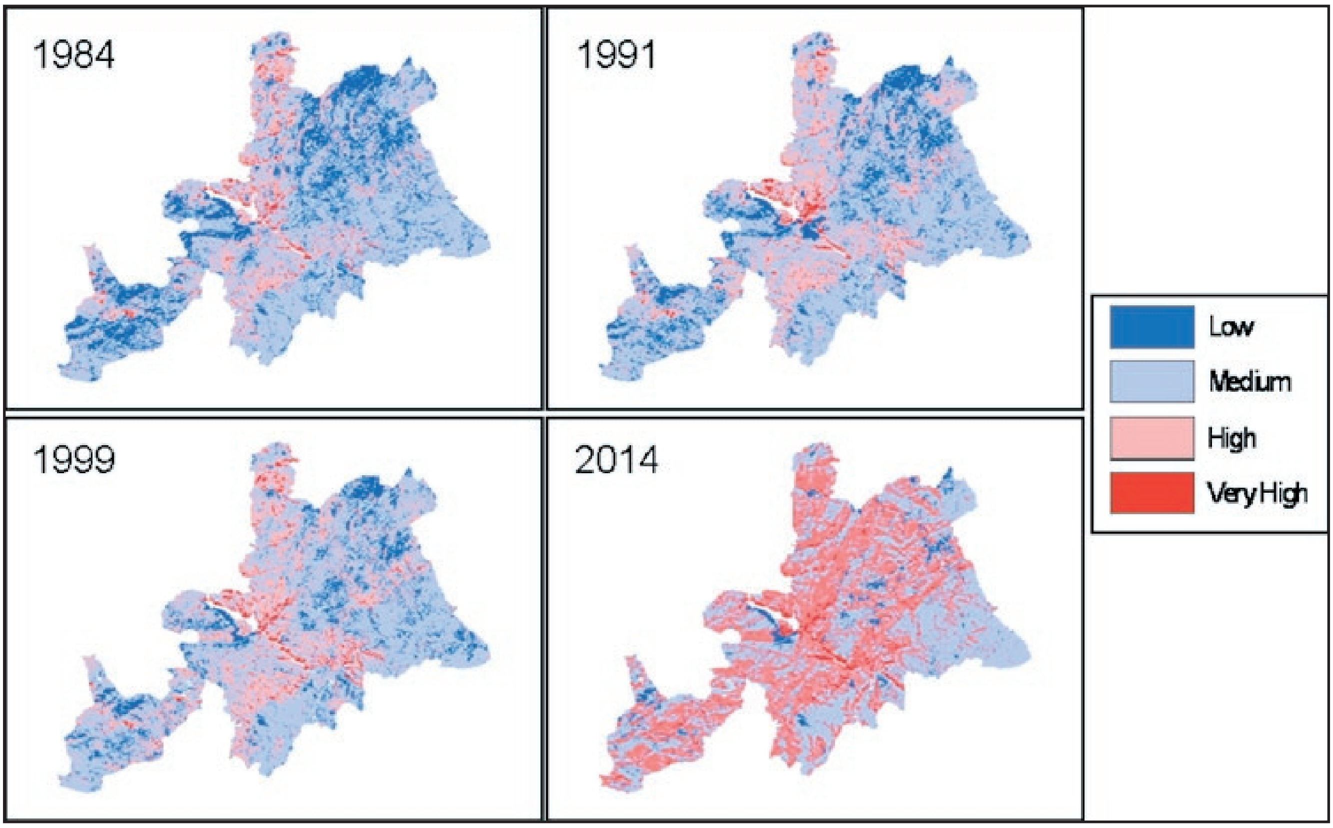

Figure 7. Wildfire risk maps produced by CONMOD. Through time the proportion of 'High' and 'Very High' risk increases, shown by the increase in light and bright red areas which fragment lower risk areas (shown in blue).

sity values prove to be greater for CONMOD and SACMOD. This is due to the more spatially heterogeneous and patchy nature of these maps (also shown by greater patch numbers in the CONMOD maps), likely due to the inclusion of the contiguity index. Contiguity was calculated at the patch-level and so introduces a further hierarchical level (grain) by which to distinguish areas of differing wildfire risk.

Discussion

Generally, wildfire risk, as estimated here, has been shown to increase during the observed period (1984-1999) across SPA 56. The use of a logistic regression model of land cover change suggests that if the observed land cover changes continue, wildfire risk will continue to rise across SPA 56 as a whole. Furthermore, decreases in the CV of risk values suggest a decreasing spatial variability of risk in the landscape (in terms of the range of risk values). Romero-Calcerrada and Perry (2004) suggested that the observed changes in SPA 56 might increase wildfire risk due to increases in highly flammable fuels and spatial homogenisation of the landscape. The findings here support this view. Increases (both observed and predicted) in shrubland cover, commensurate with decreases in pasture, have resulted in increased wildfire risk.

The importance of increasing homogeneity in the landscape, and the consideration of landscape pattern in general in wildfire risk models of this type, is highlighted when the results of the two models are compared. CONMOD shows marked increases in the higher risk classes compared to SACMOD, suggesting that consideration of the spatial pattern does modify wildfire risk assessment. These changes are consistent with theory, i.e. that increasing landscape homogeneity increases wildfire risk. CONMOD is an improvement on SACMOD as it decreases the homogeneity of risk classes across the landscape, emphasising differences in risk between areas more clearly. In risk terms, this means putting greater emphasis on the upper risk classes ('High and 'Very High') compared to the 'Medium' risk class. In spatial terms, this means large contiguous areas of the 'Medium' risk class across the landscape are fragmented by the other risk classes. In both cases this allows wildfire and forestry managers to target areas in higher wildfire risk more accurately and therefore (hopefully) manage the landscape more effectively and efficiently.

The outcomes of this modelling strongly suggest that there is a need for improved consideration of the spatial structure of the landscape in models of this type (frequently used by risk managers on a daily and weekly basis). If not included, changes in the spatial complexity of the configuration of landscapes (e.g. homogenisation) cannot be considered. More spatially oriented approaches will allow more explicit representation of the pattern and process interactions which landscape ecologists stress as being of vital importance, especially in terms of disturbance (Turner 1989). Further, the methodology presented here shows that these types of model can be used to examine how wildfire risk might change in the future as a result of changing environmental conditions, for example climatic or land cover change. Convenient measures for assessing wildfire hazard, and potential changes in that hazard, at larger regional and continental extents have recently been called for and explored (e.g. Malamud et al. 2005). The approach taken here is not the most mechanistic consideration of the potential changes in processes as a result of these types of changes (or interactions between these changes, for example changes in vegetation growth rates with changing climate, Osborne et al. 2000). However, it provides a quick and simple tool for assessing risk, and is transferable to other Mediterranean landscapes.

Summary

GIS-based models have been used previously to assess wildfire risk in Mediterranean environments. Here two such models, one used previously (SACMOD, Salas and Chuvieco 1994) and an extended version of this that considers the spatial configuration of the landscape (CONMOD), showed that wildfire risk has increased in the study area (SPA 56 'Encinares del río Alberche y Cofio', central Spain). This increase is largely due to due to increases in scrubland and commensurate decreases in pastureland, allied with increasing homogeneity of the landscape driven largely by agricultural abandonment (as suggested by Romero-Calcerrada and Perry 2004). However, the results suggest that CONMOD highlighted changes in the spatial structure of the landscape (i.e. increased homogeneity) better than SACMOD. Further, both models were used to examine potential changes in future wildfire risk based on regression model-derived predictions of future land cover. The results suggest that wildfire risk will continue to increase across the landscape. Finally, it is suggested that a methodology such as that used here could be used in other Mediterranean landscapes for the rapid assessment of current and future wildfire risk.

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