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Environmental drivers and spatial dependency in wildfire ignition patterns of northwestern Patagonia

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ABSTRACT

Fire management requires an understanding of the spatial characteristics of fire ignition patterns and how anthropogenic and natural factors influence ignition patterns across space. In this study we take advantage of a recent fire ignition database (855 points) to conduct a comprehensive analysis of the spatial pattern of fire ignitions in the western area of Neuquén province (57,649 km^2), Argentina, for the 1992–2008 period. The objectives of our study were to better understand the spatial pattern and the environmental drivers of the fire ignitions, with the ultimate aim of supporting fire management. We conducted our analyses on three different levels: statistical "habitat" modelling of fire ignition (natural, anthropogenic, and all causes) based on an information theoretic approach to test several competing hypotheses on environmental drivers (i.e. topographic, climatic, anthropogenic, land cover, and their combinations); spatial point pattern analysis to quantify additional spatial autocorrelation in the ignition patterns; and quantification of potential spatial associations between fires of different causes relative to towns using a novel implementation of the independence null model. Anthropogenic fire ignitions were best predicted by the most complex habitat model including all groups of variables, whereas natural ignitions were best predicted by topographic, climatic and land-cover variables. The spatial pattern of all ignitions showed considerable clustering at intermediate distances (<40 km) not captured by the probability of fire ignitions predicted by the habitat model. There was a strong (linear) and highly significant increase in the density of fire ignitions with decreasing distance to towns (<5 km), but fire ignitions of natural and anthropogenic causes were statistically independent. A two-dimensional habitat model that quantifies differences between ignition probabilities of natural and anthropogenic causes allows fire managers to delineate target areas for consideration of major preventive treatments, strategic placement of fuel treatments, and forecasting of fire ignition. The techniques presented here can be widely applied to situations where a spatial point pattern is jointly influenced by extrinsic environmental factors and intrinsic point interactions.

1. Introduction

Fire management requires an understanding of the spatial characteristics of fire ignition patterns and a quantification of the relative importance of anthropogenic and natural factors on ignition probabilities across space and time (Finney, 2005; Thompson et al., 2012). This is an important task because fire is a major driver of the structure and composition of vegetation communities in many ecosystems, and vegetation (fuels) has a strong potential to exert feedbacks on fire occurrence patterns (Whelan, 1995; Bond and van Wilgen, 1996; Mermoz et al., 2005). For this reason, wildfires have been intensively studied around the globe, but also because of their general importance for the global carbon cycle (Bowman et al., 2009; USGCRP, 2011). In the last five years, many studies have been published in this research field, ranging from those with a global perspective (e.g. Krawchuk et al., 2009) to those focussed on different continents or specific areas such as Africa (Dlamini, 2010), Asia (Liu et al., 2011), Europe (mainly the Mediterranean region) (Romero-Calcerrada et al., 2008; Catry et al., 2009; Martínez et al., 2009; Bar Massada et al., 2012; Oliveira et al., 2012; Serra et al., 2013), North America (Syphard et al., 2008; Parisien and Moritz, 2009; Gralewicz et al., 2012) and Oceania (O'Donnell, 2011).

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The most common approach for understanding the spatial pattern of wildfire ignitions and their environmental drivers is statistical modelling based on observed ignition locations (Sturtevant and Cleland, 2007; Bar Massada et al., 2011) which is closely related to species-distribution modelling (Franklin, 2010). Observed wildfire ignition locations (analogous to locations of species occurrence) are analysed in relation to environmental variables that are hypothesised to influence the spatial distribution of ignitions (or species occurrences) (Bar Massada et al., 2012). Application of this approach showed that the occurrence of fire ignitions is inherently stochastic, but that abiotic and biotic factors affect the location of fire ignitions and the size of the fires (i.e. environmental dependency). For example, fuel characteristics and topography are major factors that determine the spatial pattern of wildfires (Guyette et al., 2002; Mermoz et al., 2005) and human activities play an important role in fire dynamics, not only in starting fires, but also by modifying fuel characteristics (Pyne, 1996; Bar Massada et al., 2012). However, additional smaller-scale autocorrelation may arise in the spatial ignition pattern if fire modifies small-scale vegetation composition in such a way that a once burned site may become more fire prone in subsequent years (Mutch, 1970; Kitzberger et al., 2012) or trees that have burned before are subject to a higher likelihood of burning than trees that have not burned before (Romme, 1980). Such a spatial autocorrelation structure in the ignition pattern that occurs additionally to the broader-scale environmental dependency can be analysed with recent methods of spatial point pattern analysis (Illian et al., 2008).

Fire is of special importance in northern Patagonia (Tortorelli, 1947; Kitzberger et al., 1997; Veblen et al., 1999; Mundo et al., 2012). While the temporal pattern of fire occurrence has been well investigated in northern Patagonia (Kitzberger et al., 1997; Veblen et al., 1999; Mundo et al., 2012), much less is known about its spatial patterns. For example, how are fire ignitions distributed across larger spatial scales and what are their natural and anthropogenic drivers? A recently compiled fire ignition database on the southern Andes of Argentina developed by the Argentinian National Plan of Fire Management (Plan Nacional de Manejo del Fuego, unpublished data) provides information on dates, causes, extent and geographical coordinates of fire ignitions together with detailed maps of environmental variables and land use provides a means for a detailed study of spatial patterns of fire ignitions.

In this study we took advantage of this fire ignition database and conducted a comprehensive analysis of the spatial pattern of fire ignitions in the western area of Neuquén province for the 1992–2008 period. The general aim of our study was to better understand the spatial patterns and the environmental drivers of these fire ignitions with the ultimate objective of supporting fire management. We conducted our analyses on three different levels.

For the first analysis we used an information theoretic approach for model selection (Burnham and Anderson, 2002) to test several *a priori* hypotheses on the environmental factors that determine fire ignition probabilities based on topographic, climatic, land cover and anthropogenic variables (e.g. Kanagaraj et al., 2011; De Angelo et al., 2013). We conducted separate analyses for all fire ignitions, and for ignitions attributed to anthropogenic and natural causes. We hypothesised that fire ignitions of natural causes (in the following "natural fire ignitions") are best predicted by a model based on natural factors (i.e. topographic and climatic variables) whereas fire ignitions of anthropogenic causes (in the following "anthropogenic fire ignitions") are best predicted by a model that combines natural and anthropogenic factors.

In a second analysis we used techniques of spatial point pattern analysis to quantify the smaller-scale correlation structure (<50 km) of the spatial pattern of the different types of fire ignitions. The statistical models selected for the first analysis were used to describe the underlying extrinsic heterogeneity of the corresponding fire ignition patterns. We hypothesised that extrinsic environmental factors alone are not sufficient to explain the spatial pattern of fire ignitions.

In a third analysis we quantify potential spatial associations between fires of different causes and of natural and anthropogenic causes relative to towns. We hypothesised that (i) there is a positive small-scale relationship (<10 km) between the location of towns and the spatial pattern of anthropogenic fire ignitions due to "diffusion" of human activities from towns, (ii) natural fire ignitions are independent of the pattern of towns, and (iii) natural fire ignitions are independent of the patterns of anthropogenic fire ignition. To test these hypotheses we present a novel implementation of the independence null model that conditions on both, the observed environmental dependency and the observed autocorrelation structure of the ignition patterns.

2. Methods

2.1. Fire ignition database

The unpublished database from the Plan Nacional de Manejo del Fuego (Argentinian National Plan of Fire Management) for Neuquén province (northern Patagonia, Argentina) was used in this study. It covers the period January 1992–January 2008 and comprises 2326 fire reports. This database was built with fire reports provided by the Dirección Provincial de Bosques (Neuquén Provincial Forest Service), volunteer fire-fighters, Administración de Parques Nacionales (National Parks Administration), Gendarmería Nacional Argentina (Argentine National Gendarmerie), Aero Clubs and the Argentinian National Plan of Fire Management. It contains the following information for each record: starting and ending time, location, coordinates, property (public or private), type of land cover affected, area burned and causes. Due to the absence of coordinates in many of these records, the original database was reduced to 855 fire reports for which coordinates were reported. The final data base comprised 153 fires caused by climatic events, 52 intentional fires, 557 caused by accident or negligence, and 93 of unknown origin.

2.2. Study area

The corners of the study area were defined by the northernmost–westernmost and southernmost–easternmost ignition points of the 855 fires reported in the Neuquén Province for the period 1992–2008. This led to a 57,649 km^2 study area ranging 36.8–40.9°S latitude and 69.7–71.7°W longitude and bordering Chile to the west, Mendoza Province to the north, and Río Negro Province to the south (Fig. 1). Mean annual precipitation ranges from 150 mm at lower elevations at the northwestern end of the study area to 1530 mm at the southwestern end of the study area. Mean annual temperature ranges from 4.5 °C in the southwest to 14 °C in the north. Elevation across the study area ranges from approximately 426–3966 m a.s.l. with Tromen Volcano as the highest peak. Vegetation in the study area reflects the west-to-east precipitation gradient, ranging from forests of *Nothofagus pumilio*, *Nothofagus antarctica*, and *Austrocedrus chilensis* in the west on the slopes of the Andes mountain range to the Patagonian steppe of shrubs and grasses, reaching the Monte Desert (dominated by *Larrea divaricata* and *Atriplex lampa*) to the east. This vegetation gradient results in substantial differences in fuel types in each land-cover class. Thirty-eight towns are located within the study area (Fig. 1), with populations ranging from 103 (Villa del Curi Leuvú) to 31,534 inhabitants (Zapala).

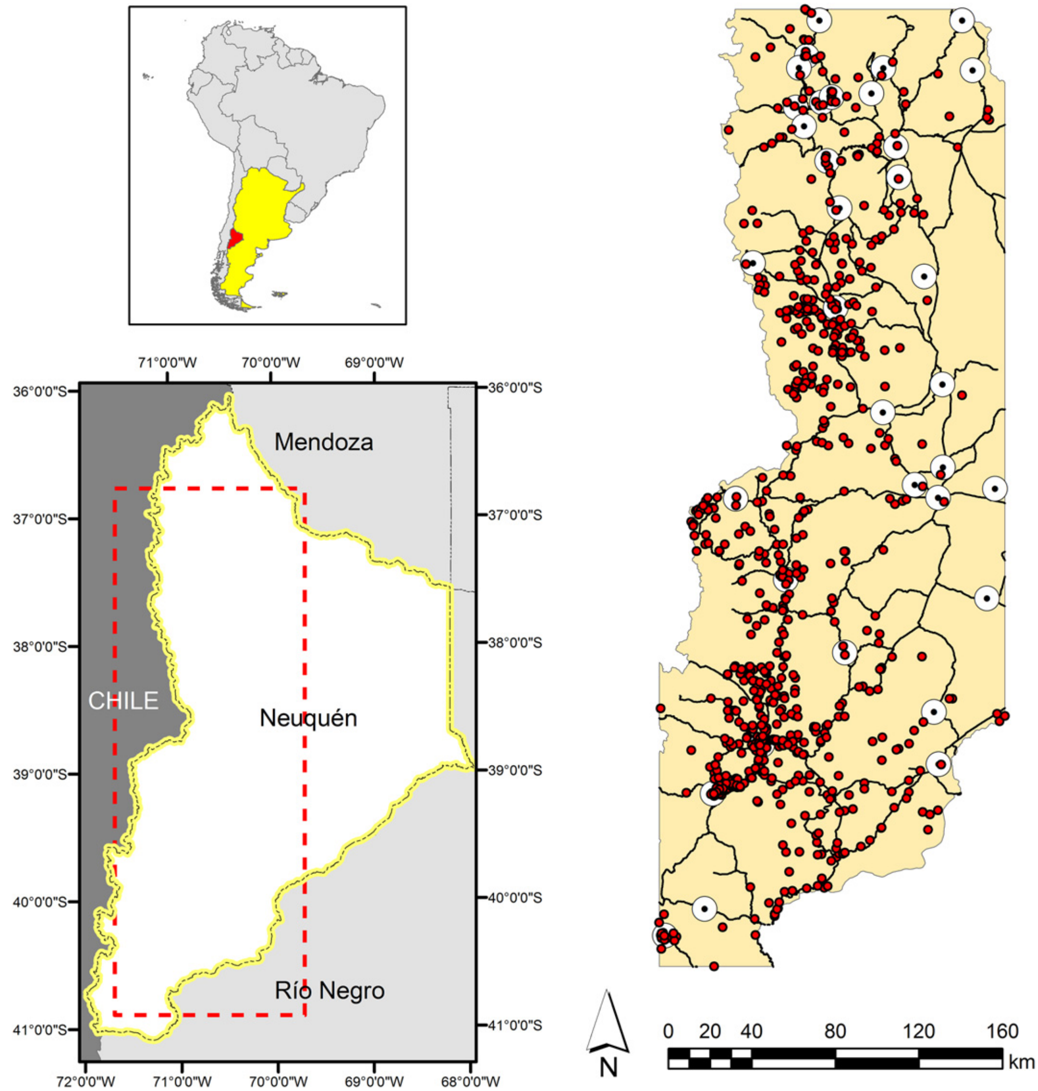

Fig. 1. Map of the study area. The graph on the left indicates the rectangular area over a map of Neuquén province. On the right, the extracted 57,649 km^2 study area used in this study. Fire ignitions are indicated in red, cities in white dotted circles and routes in black lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3. Variable preparation

All environmental variables were expressed in raster format using a grid resolution of 90 m (see Fig. S1 And Table S1 In Supporting information). Environmental variables encompassed four groups: topographic variables (elevation, northing, easting, slope, distance to streams), climatic variables (mean annual temperature, annual precipitation), anthropogenic variables (distance to roads and towns, diffusion of human activity from towns), and 13 categorical land-cover classes (Tables S1 and S2). Diffusion of human activity away from towns was quantified as the number of towns and population density within different distances R (see Appendix S1 for detailed description of methods). We tested several neighbourhood distances between 5 and 50 km (i.e. $R = 5$, 10, 20, 30, 40 and 50 km) to detect a critical scale of neighbourhood diffusion.

Because fire ignitions are spatially autocorrelated (Fig. 1), we also incorporated a spatial autoregressive term in the model of fire occurrence probability (Chou et al., 1993; Appendix S1). We tested autoregressive variables based on several neighbourhoods (i.e. $R = 0.5$, 1, 1.5, 2 and 2.5 km) to determine the spatial scale that received most support from our data.

2.4. Statistical analyses to determine the probability of a fire ignition (analysis 1)

2.4.1. GLM and generation of pseudo-absences

We used statistical habitat models based on Generalised Linear Models (GLM) to predict the probability of a fire ignition from a set of landscape-scale explanatory variables and presence versus pseudo-absence data (Manly et al., 1993). Coordinates for pseudo-absences were randomly but regularly distributed within the study area (having a minimal distance of 8 km) because an ignition could occur, in principle, at any location. However, to avoid pseudo-absence points being located close to observed fire ignition points, we did not allow pseudo-absence points within buffer zones of 500 m around fire ignition points. As recommended by Liu et al. (2005), we selected the number of pseudo-absences similar to the number of presences to obtain a dataset with a prevalence of 50%.

To account for our data structure we used logistic regression (McCullagh and Nelder, 1989) to predict the probability $p(\mathbf{x})$ of fire ignition at a given location x within the study area based on a set of independent variables $v_i(\mathbf{x})$. Once the model is fitted, probability values can be calculated for each location $\mathbf{x}$ within the study area. All GLMs were fitted within the program R 2.8.1 (R Development Core Team, 2008).

2.4.2. Model selection

We derived a set of six alternative *a priori* hypotheses on the different types of factors that may influence the occurrence of a fire: topography, climate, anthropogenic, natural (i.e. topography + climate), natural + land cover, and all factors together (Table 1). We evaluated these six hypotheses separately for all fire ignitions, and fire ignitions due to natural and anthropogenic causes, yielding a total of 18 models. Before running the GLMs, we performed a variable reduction within each hypothesis to avoid inclusion of highly correlated variables and variables that did not show differences between presence and pseudo-absences (Appendix S1). We selected the most parsimonious model from competing models based on the lowest Akaike Information Criterion (AIC). To assess the prediction accuracy of the models we performed a receiver operating characteristic (ROC) analysis (Fielding and Bell, 1997) and used the overall area under the curve (AUC) as index of model prediction. For the ROC analysis we used correctly classified presences (i.e. observed fire ignitions) and correctly classified pseudo-absences.

We finally applied the selected model of each group (i.e. all ignitions, natural and anthropogenic causes) to the entire study area (without the autoregressive term) using the predicted coefficients and the GIS map layers of the explanatory variables to convert our model into a predictive map surface. This map, which gives the probability that an ignition would occur at location x, was then used in the point pattern analysis as intensity function $\lambda(x)$ to describe the heterogeneity of the pattern.

2.4.3. Two-dimensional model

We expect that natural and anthropogenic caused ignitions are driven by different factors. Revealing the areas where the risk for the occurrence of the two types of ignitions is different or similar is of high importance for management because they require different management actions. To reveal such areas we used the Naves scheme (Naves et al., 2003) that classifies the ignition probability at location $\mathbf{x}$ in a two-dimensional way based on two axis, one based on the model for fire ignitions of natural causes $[=p_{\mathrm{nat}}(\mathbf{x})]$ and the other being that of anthropogenic causes $[p_{\mathrm{anth}}(\mathbf{x})]$. To obtain a simple classification, we divided each axis into low risk ($p \leq 0.1$), moderate risk ($0.1 < p \leq 0.5$) and high risk ($p > 0.5$). This resulted in four classes that require especial attention (see inset Fig. 2d): areas of overall high fire risk (i.e. $p_{\mathrm{nat}} > 0.5$ and $p_{\mathrm{anth}} > 0.5$), areas of moderate fire risk (i.e. $0.1 < p_{\mathrm{nat}} < 0.5$ and $0.1 < p_{\mathrm{anth}} < 0.5$), areas of high natural but moderate anthropological risk (i.e. $p_{\mathrm{nat}} > 0.5$ and $p_{\mathrm{anth}} < 0.5$), and areas of moderate natural but high anthropological risk (i.e. $p_{\mathrm{anth}} > 0.5$ and $p_{\mathrm{nat}} < 0.5$).

2.5. Spatial point pattern analysis (analyses 2 and 3)

The spatial pattern of fire ignitions (Fig. 1) is apparently a heterogeneous point pattern where the probability $\lambda(\mathbf{x})$ that a fire ignition occurs at location $\mathbf{x}$ depends on the environmental conditions at the location $\mathbf{x}$. However, the spatial pattern of fire ignitions shows also a considerable aggregation which is probably not captured by broader-scale environmental variables (Fig. S1), but caused by intrinsic mechanisms either in fire susceptibility or in some form of autocorrelation in human behaviour (not captured by our environmental variables). The first objective of the point pattern analysis is therefore to quantify this observation and to test if intrinsic mechanisms are required to explain the observed patterns of fire ignitions (analysis 2). The second objective of point pattern analysis is to test several specific hypotheses on the spatial dependency among the pattern of different fire causes and of fire ignitions to towns (analyses 3).

2.5.1. Summary statistics

To quantify the spatial association between two patterns such as towns (focal pattern i) and fire ignitions (second pattern j) we used the bivariate neighbourhood density function $O_{ij}(r)$ which is the mean density of fire ignitions within rings with width dr and radius r centred at towns (Wiegand and Moloney, 2004). Using rings has the advantage that one can isolate specific distance classes, whereas the commonly used cumulative K-function confounds effects at larger distances with effects at shorter distances. Additionally, the O-ring statistic has the direct interpretation of a neighbourhood density, which is more intuitive than an accumulative measure (Wiegand and Moloney, 2004). Important additional information is provided by the distribution function $D_{ij}(r)$ of the distances r from fire ignitions to the nearest town (Illian et al., 2008). Nearest neighbour statistics are "short-sighted" and sense only the immediate neighbourhood of the points, which makes them especially sensitive to local cluster structures. The corresponding univariate (or partial) summary statistics $O_{jj}(r)$ and $D_{jj}(r)$ for the pattern of ignitions (j) follow intuitively by estimating the density of ignitions at distance r (or the distance r to the nearest ignition) for all ignitions (Illian et al., 2008). All point pattern analyses were conducted with the software *Programita* (Wiegand and Moloney, 2004). Because the study area showed an irregular shape (Fig. 1) we used a polygon encompassing the study area to exclude the area outside the study area. For the estimation of the summary statistics and the intensity function we used a spatial resolution of 1 km and a ring width of 3 km.

2.5.2. Null models for univariate point pattern analysis (analysis 2)

Our null hypothesis is that the univariate patterns of fire ignitions (all, natural and anthropogenic causes) were only driven by

Table 1
The six hypotheses to predict the probability of fire occurrence and corresponding environmental variables.

ID	Hypothesis	Variables
1	Topographic	Elevation, northing, easting, slope, distance to streams, and autoregressive variable
2	Climatic	Precipitation, temperature and autoregressive variable
3	Anthropogenic	Distance to roads, distance to towns, number of town in different range of distances (2, 5 and 10 km), number of habitants in different range of distances (5, 10, 20, 30, 40 and 50 km) and autoregressive variable
4	"Natural" (1 + 2)	Elevation, northing, easting, slope, distance to streams, precipitation, temperature and autoregressive variable
5	"Natural" + Land cover	Elevation, northing, easting, slope, distance to streams, precipitation, temperature, land cover and autoregressive variable
6	Full	Elevation, northing, easting, slope, distance to streams, precipitation, temperature, land cover, distance to roads, distance to towns, number of town in different range of distances (2, 5 and 10 km), number of habitants in different range of distances (5, 10, 20, 30, 40 and 50 km) and autoregressive variable

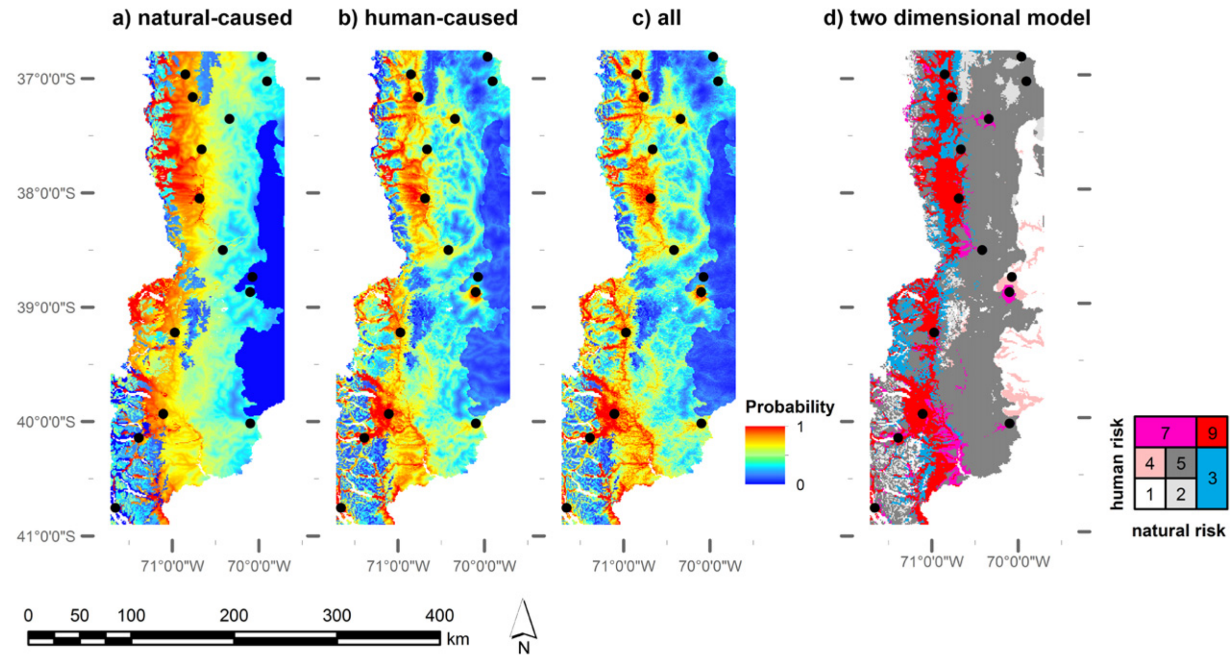

Fig. 2. Probability of occurrence of fire ignitions as estimated by the most parsimonious logistic regression models in the 1 km resolution used for the point pattern analyses. a) Model for natural-caused fire ignitions only based on all groups of variables except anthropogenic variables, b) model for human-caused fire ignitions only based on the full model, c) model for all fire ignitions based on the full model. For best models see Table A3. d) Two-dimensional model that visualises the differences between the risk of fire ignitions due to natural vs. anthropogenic causes. The probability cut-offs: low risk: 0.1, intermediate human risk: 0.47, intermediate natural risk: 0.5. In all panels, a black dot indicates a town with a population of 1000 or more.

environmental heterogeneity quantified by the corresponding intensity function $\lambda(\mathbf{x})$ calculated in analysis 1. To test this hypothesis we used a heterogeneous Poisson process (Wiegand and Moloney, 2004) as null model in which the observed fire ignitions were randomised independently from each other but the probability that location $\mathbf{x}$ received a ignition was proportionally to $\lambda(\mathbf{x})$ (e.g. Yang et al., 2007; Fig. S2A and C).

2.5.3. Null models for bivariate point pattern analysis (analysis 3)

To respond to our three hypotheses regarding the spatial associations between the fires of different origin and their relationship to towns we need to test for independence of two patterns. A test of independence must be conditionally on the spatial structure of the two univariate component patterns, but any relationship between the component patterns need to be removed (Dixon, 2002; Jacquemyn et al., 2012). However, this is a difficult task due to the potential dependence of the distribution of fire ignitions on environmental conditions. To reveal the "pure" second-order (interaction) effect we therefore used a novel implementation of the independence null model that conditions on both, the observed small-scale autocorrelation structure of the fire ignitions and the environmental dependency represented by the intensity function $\lambda(\mathbf{x})$. To this end we used pattern reconstruction (Tscheschel and Stoyan, 2006; Wiegand et al., 2013) that allow generation of patterns that follow a given intensity function $\lambda(\mathbf{x})$ and show in good approximation the same small-scale autocorrelation structure as the observed pattern (Appendix S1).

In hypothesis i (location of town vs. anthropogenic fire ignitions) and hypothesis ii (location of town vs. natural fire ignitions) we kept the pattern of towns fixed (because it was not influenced by fires that occurred between 1992 and 2008) and randomised the pattern of anthropogenic or natural fire ignitions, respectively, based on pattern reconstruction using the corresponding fire intensity function as explained above. In hypothesis iii (anthropogenic vs. natural fire ignitions) we conducted two analyses allowing each pattern being the focal pattern (i.e. anthropogenic vs. natural fire ignitions and natural vs. anthropogenic fire ignitions).

2.5.4. Significance tests

To assess the fit of the independence null model, we generated 199 simulated data sets and used the 5th lowest and highest values of our summary statistics [i.e. $O_{ij}(r)$ or $D_{ij}(r)$] at distance r as simulation envelopes to depict the range of possible values under the point process model. The simulation envelopes provide approximate 5% intervals but are prone to type I error (Diggle, 2003; Loosmore and Ford, 2006; Illian et al., 2008). To assess the overall fit of the independence null model we therefore used a goodness-of-fit (GoF) test proposed by Loosmore and Ford (2006). This test reduces the distance-dependent information of the summary statistics for the observed data ($k = 0$) and the simulated data ($k = 1, \ldots, 199$) into one single test statistics u_k and calculates the rank of the observed u_k ($k = 0$) within all u_k. If the rank of u_0 is larger than 190 the data show a departure from the null model with a 5% error rate.

3. Results

3.1. Analysis of fire ignition database

Sixty-five percent of the 855 fire ignitions were caused by accident or negligence, 18% by climatic events (i.e. lightning), 7% by arsonists and in 10% of cases the cause was unknown. The 855 ignitions burned a total area of 366,440 ha and 78% of the ignitions burned areas of less than 30 ha. Climatic events accounted for 53% of the total area burned (193,126 ha), and negligence for 44% (160,635 ha). Thus, although the number of ignitions differed, fires from natural and anthropogenic causes burned approximately the same area.

The ignitions were not randomly distributed over the different land cover types after correcting for the area of each land cover type

(Chi-Square = 3601.738; df = 12 and $p < 0.01$). The Patagonian steppe, wetlands, tree plantations and urban areas showed more ignitions than expected by chance whereas Monte Desert, *N. pumilio* forests, rocky areas, and High-Andean vegetation showed less ignitions than expected.

3.2. Mapping fire ignition probability (analysis 1)

The six competing models (Table 1) received different levels of support from the data (Table 2). Natural fire ignitions yielded generally poorer models than anthropogenic fire ignitions, which may be a consequence of the smaller sample size (153 vs. 619). Natural ignitions were best predicted by all natural factors (i.e. topographic, climatic and land cover variables), whereas anthropogenic and topographic factors yielded the poorest models (Table 2A). However, the full model that included all factors failed only marginally (ΔAIC = 2.5; Table 2A). Annual precipitation and the spatial autoregressive term were the only significant variables in the natural ignition model (Table S3).

Anthropogenic fire ignitions were best predicted by the full model whereas model 3, based only on anthropogenic factors, yielded the poorest model (Table 2B), but still explained 74% of the data correctly (vs. 78% with the full model). Annual precipitation, distance to roads and streams, elevation, northing, population density within 20 km, land cover 7 (i.e. Patagonian steppe) and the spatial autoregressive term (with $R = 1.5$ km) were significant in the full model for anthropogenic fire ignitions. The only significant variable with negative effect was elevation. In absolute terms, land cover 7 (i.e. Patagonian steppe) was the strongest predictive variable (Table S3).

The full model 6 also received most support for all fire ignitions (Table 2C). It was very similar to the full model of anthropogenic fire ignitions in both significant variables and coefficients, but it contained four more significant variables. The probability of a fire ignition was higher if northing was lower and influenced by land covers 2, 7, 8 and 11 (i.e. *Araucaria* forests, Patagonian steppe, wetlands and forest plantations). In absolute terms, land cover 11 (i.e. forest plantations) was the strongest predictive variable and it affected the ignition probability positively.

The maps of the three final models show how the predicted ignition probabilities vary across the study area (Fig. 2). Sixteen percent of the study area shows high natural and human fire risk (red in Fig. 2d) located in a clumped way along a N–S belt across Neuquén Province, 10% of the region shows high natural ignition risk but moderate risk of anthropogenic fire ignitions (light blue), and 4% of the area shows high risk of anthropogenic fire ignitions but moderate risk of natural ignitions (magenta, Fig. 2d). The model of natural ignitions indicates a distinct N–S band of high risk for fire ignitions at longitudes between c. 70°30′W and 71°30′W (Fig. 2a). Andean regions in northern Neuquén (N of Aluminé) show a high risk, whereas the Lake District towards the south shows a lower risk of natural ignitions. Here, the highest risk band is restricted to intermediate levels of precipitation along the west–east transition (Fig. 2a). Anthropogenic ignitions show a high risk in a N–S band located along the ecotonal area with several foci concentrated around highly populated areas (dots in Fig. 2b). Nevertheless, both high human- and natural-ignition risk show a large area of juxtaposition, surrounded by areas of high natural fire risk.

3.3. Spatial pattern of all, human-caused and natural ignitions (analysis 2)

The spatial pattern of all ignitions ($n = 855$) showed considerable clustering at distances below 50 km (Fig. 1) not captured by the probability of fire ignitions derived in analysis 1 (Fig. 3A). The heterogeneous Poisson null model accounted for only a small increase in the neighbourhood density relative to the overall intensity λ (cf. grey line with solid black horizontal line in Fig. 3A). There was a substantial additional clustering at distances below 10 km (with neighbourhood densities more than 3 times higher than expected by the null model) and a second critical scale of clustering of 35 km is visible where local density is more than 1.5 times higher than expected by the null model (Fig. 3A). The nearest neighbour distribution function (inset Fig. 3A) shows that 35% of all ignitions have at least one neighbour within 1 km, and 60% within 2 km and only at distances greater than 8 km is the heterogeneous Poisson null model met. The results for fire ignitions of anthropogenic causes mainly reflect that of all ignitions (Fig. 3B). The results for

Table 2
Results of the statistical models predicating the probability that a fire ignition occurs at a given location in study area.

Model	1.Topographic	2.Climatic	3.Anthropogenic	4.Natural	5.Natural + landcover	6.Full
A) Natural fire ignitions						
AIC	377.2	366.8	378.8	366.8	**346.2**	348.7
Delta AIC	31	20.6	32.6	20.6	0	2.5
AUC	0.676	0.723	0.701	0.716	0.792	0.796
Cut-off	0.461	0.439	0.442	0.454	0.500	0.504
Sensitivity	0.575	0.601	0.719	0.595	0.686	0.68
Specificity	0.647	0.608	0.536	0.601	0.693	0.686
Full[a]	0.611	0.605	0.627	0.598	0.690	0.683
B) Anthropogenic fire ignitions						
AIC	1329.2	1327	1356.6	1262.8	1210	**1205.1**
Delta AIC	124.1	121.9	151.5	57.7	4.9	0
AUC	0.796	0.806	0.806	0.832	0.855	0.859
Cut-off	0.414	0.403	0.388	0.43	0.471	0.472
Sensitivity	0.698	0.696	0.735	0.753	0.772	0.774
Specificity	0.699	0.698	0.738	0.755	0.773	0.776
Full[a]	0.699	0.697	0.736	0.754	0.773	0.775
C) Complete fire record						
AIC	1832.9	1824.2	1849.3	1741.7	1653.7	**1638.7**
Delta AIC	194.2	185.5	210.6	103	15	0
AUC	0.788	0.793	0.795	0.825	0.851	0.855
Cut-off	0.407	0.400	0.399	0.425	0.460	0.461
Sensitivity	0.699	0.678	0.718	0.743	0.766	0.771
Specificity	0.700	0.682	0.719	0.742	0.767	0.770
Full[a]	0.700	0.68	0.719	0.743	0.766	0.771

[a] % cases correctly predicted.

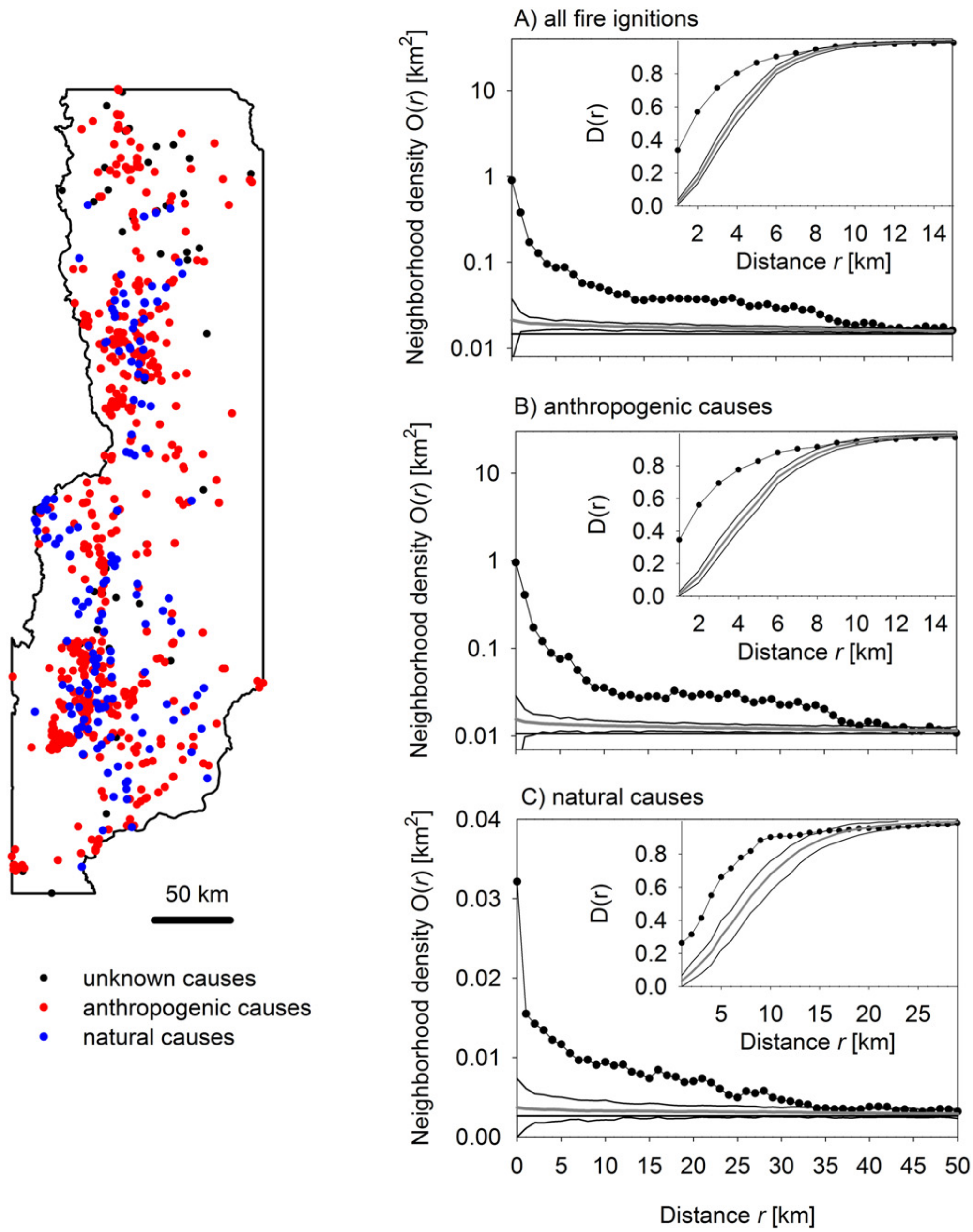

Fig. 3. Results of the univariate analysis for the different fire ignition patterns using the heterogeneous Poisson process based on the corresponding models of fire ignition probability. Note the logarithmic scales in A) and B). Closed circles: observed summary statistic, bold grey line: expectation of the heterogeneous Poisson null model, black lines: simulation envelopes being the 5th lowest and highest values taken from the 199 simulations of the null model, solid horizontal line: overall intensity of fire ignitions.

the fire ignitions of natural causes were similar to those for anthropogenic causes, but the local clustering was substantially lower.

3.4. Bivariate point pattern analysis (analysis 3)

3.4.1. Location of town vs. anthropogenic fire ignitions

Fire ignitions showed a highly significant small scale ($<$5 km) attraction to towns, the density of fire ignitions increased linearly with increasing proximity to towns (Fig. 4B). At distance of 1 km, the density of ignitions was five times higher than expected by chance. The nearest neighbour distribution function showed a somewhat weaker departure from the null model but was still significant (i.e. $p = 0.045$ for the 1–50 km interval); 37% of all towns had fire ignitions within 1 km compared to a 18% expected by the null model (inset Fig. 4A). Thus, the attraction was mostly an effect of elevated density around approximately 20% of the towns (=5–6 towns). The results for the data set of all fires were similar (Fig. 4A).

3.4.2. Location of town vs. natural fire ignitions

As expected, the density of fire ignitions due to natural causes were independent from that of towns (Fig. 4C; $p = 0.32$ for the 0–50 km interval). However, the distances from towns to the nearest fire of natural causes were somewhat larger than expected (inset Fig. 4C; $p = 0.03$ for the 0–50 interval).

3.4.3. Anthropogenic vs. natural fire ignitions

The shape of the expectation of the null model (grey line in Fig. 4D) relative to the overall density of fire ignitions of anthropogenic causes (black horizontal line in Fig. 4D) indicates that the

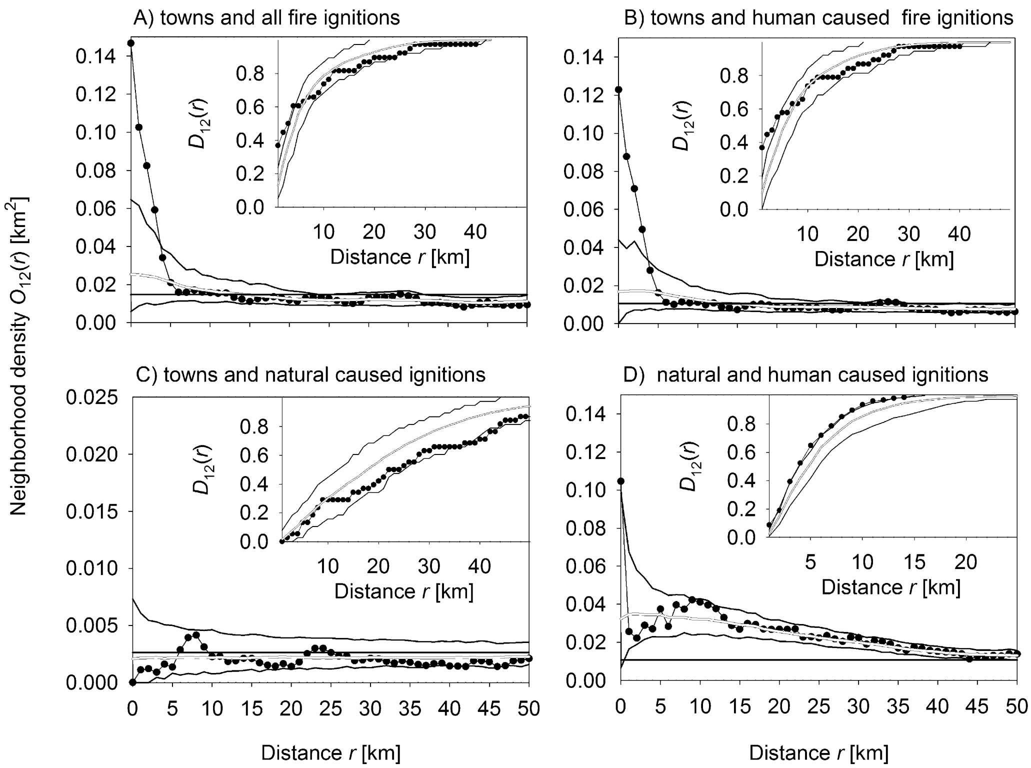

Fig. 4. Results of the bivariate analysis of testing for independence of fire ignitions from towns (A–C) and independence of fire ignitions of anthropogenic and natural causes (D). The null model fixed the first pattern and randomised the second pattern conditioning on the observed intensity function and univariate spatial structure (using pattern reconstruction). Closed circles: observed summary statistic, bold grey line: expectation of the heterogeneous Poisson null model, black lines: simulation envelopes being the 5th lowest and highest values taken from the 199 simulations of the null model, solid horizontal line: overall intensity of the second pattern.

null model incorporated a substantial "habitat-driven" attraction of both types of ignitions. The neighbourhood density of fire ignitions of anthropogenic causes around that of natural causes was approximately three times higher than expected by completely independent patterns (i.e. no shared habitat preference). This was expected because the best model for fire ignitions of anthropogenic causes included the natural factors.

When factoring out the first-order "habitat effect" with the independence null models based on pattern reconstruction and the fire intensity estimate $\lambda(\mathbf{x})$, the neighbourhood density function revealed that fires of natural and anthropogenic causes were independent for both situations, the natural (pattern 1) – anthropogenic (pattern 2) pair (Fig. 4D; $p = 0.35$; $p = 0.16$) and for the reversed situation ($p = 0.165$). The nearest neighbour distribution function supported independence for the anthropogenic (pattern 1) – natural (pattern 2) pair ($p = 0.72$), but yielded for the reversed situation a slight attraction of fire ignitions of anthropogenic causes around those of natural causes (inset Fig. 4D; $p = 0.035$).

4. Discussion

In this study we conducted a detailed analysis of the environmental dependency and spatial patterns of fire ignitions of anthropogenic and natural causes in the western part of Neuquén province, Argentina. Analysis of the environmental drivers clearly showed that natural factors were the most important determinants of fire ignitions which were entered into the best models for both fire ignitions due to natural causes (i.e. lightning) and due to anthropogenic causes. However, the best model for anthropogenic fire ignitions included additional variables related to human activity. Consequently, a large superposition of risks exists with more than half of the high risk areas showing high risk in both the natural and the anthropogenic model and approximately 40% only in the natural model. However, when factoring out the environmental dependency, fires of natural and anthropogenic causes occurred independently. Interestingly, the pattern of fire ignitions, and especially that of anthropogenic fire ignitions, showed considerable aggregation not accommodated by environmental factors. This may be attributed to spatial autocorrelation in human behaviour or landscape modifications of burned areas that favour re-appearance of fires. We also found a strong smaller-scale (<5 km) attraction of fire ignitions of anthropogenic causes to towns, but not for those of natural causes.

4.1. Factors favouring fire occurrence

Although our full model indicated that fire ignitions were mainly related to the distribution of human activities, fire ignition probability was also influenced by biophysical variables. This was expected because fire spread is ultimately a function of vegetation characteristics, climate, and terrain (Pyne, 1996). This fact reinforces the idea of interaction between these variables (wildland fuel, topography and weather) for starting a fire (Agee, 1993).

In all three selected models, the spatial autocorrelation term and annual precipitation had a significant and positive influence on the occurrence of a fire ignition. In absolute terms, the autoregressive term had a higher influence on fire ignition than annual precipitation. This indicates that neighbourhood effects play a key role in the distribution of fire ignitions. This finding was also observed in previous studies (Chou et al., 1993) and has important implications for wildfire management (see below). On the other hand, the positive effect of precipitation might be related to fuel build-up.

Wetter sites show higher biomass productivity than dryer sites. As a consequence, fires will tend to occur on wetter sites that accumulate more fuels for burning. In our study, such optimal areas were revealed in the eastern portion of steppe and woodlands. Towards the east, the Monte Desert has a low number of ignitions due to its lower productivity, whereas the forests, towards the west, have a lower quantity of fine fuels and, in consequence, less fire ignition opportunities.

The significance of land-cover variables in the full model reflects the variables that showed more ignitions than expected by chance: Patagonian steppe (LC 4), wetlands (LC 8), forest plantations (LC 11), *Araucaria araucana* forests (LC 2) and urban areas (Table S3). Fine fuels are readily produced and can (in the absence of overgrazing) accumulate in the Patagonian steppe and wetlands. In the wetlands, the dry summer season can produce highly flammable fuels. Forest plantations (mainly *Pinus ponderosa* and *Pinus contorta*), besides being considered inherently very flammable, have received little silvicultural treatments in recent decades and have therefore accumulated a substantial amount of flammable fuel leading to increased ignition probabilities. *A. araucana* forests showed a significant effect in the model of all fire ignitions. This result coincides with previous studies that suggested important interactions between human activities and climate forcing of fire occurrence (González and Veblen, 2006; Mundo et al., 2012). The positive effect of population density within 20 km on ignition probability found in our study is in agreement with the analysis of foci concentration around urban areas that revealed a significant inverse relationship between fire ignitions and socioeconomic indicators (i.e. more fires occurred where there is more poverty) (De Torres Curth et al., 2012).

Surprisingly, the effect of topography on fire occurrence was contrary to our expectations. North-facing slopes, which show high radiation in the southern hemisphere, reduced the probability of fire occurrence. This suggests an overriding influence of fuel accumulation (higher in the wetter south-facing slopes) over fuel desiccation (higher in drier north-facing slopes) in controlling fire ignition probabilities.

4.2. Implications for management

The spatial point analyses and the fire ignition probability maps developed in this study can be used to inform wildfire management strategies in the western area of Neuquén province. The two-dimensional model allows fire managers to delineate target areas for major preventive treatments, strategic placement of fuel treatments, and forecasting of fire ignition. Our results suggest that fire management strategies in this northern part of Patagonia should be centred on areas of overall high risk of fire ignitions (i.e. red areas in Fig. 2d), but should especially consider critical areas which are usually not detected with one-dimensional models. First, avoid fire ignitions in areas with high probability of human ignitions and low natural risk (magenta in Fig. 2d) and second, monitor areas with high probability of natural caused fires and low and high human risk. The peri-urban areas of Zapala (the most populated city in the study area), San Martín de los Andes, Chos Malal and the Collón Curá valley are clear examples of areas where fire ignitions should be controlled. Education of the general public and of decision-makers is one of the most effective solutions for preventing and mitigating human-caused fire ignitions in those areas (McCaffrey, 2004). Due to limited resources, major efforts should be concentrated around human populations and high conservation value areas located within the light blue and red areas in Fig. 2d. Specifically, controls might be aimed at the N–S band at longitudes between c. 70°30′W and 71°30′W that shows high natural risk, the peri-urban areas of San Martín de los Andes – Junín de los Andes, Loncopué and the eastern area of Lanín National Park and northeastern portion of Nahuel Huapi National Park. *Pinus* plantations in the high natural risk area require specific silvicultural treatment to reduce fuel (Johnson and Peterson, 2005) and new conifer forest plantation should not be promoted in these areas.

To be able to separate fire ignitions of different causes we did not investigate temporal trends in the occurrence of fire ignitions as done by others (e.g. Podur et al., 2003; Preisler et al., 2004; Genton et al., 2006; Hering et al., 2009). Our results can therefore inform management on general trends in fire risk expected under average environmental conditions, but such trends may sometimes be overridden by extreme climatic events such as droughts which are not covered by the environmental variables used here. Indeed, Veblen et al. (2008) demonstrated that the number of natural fires has been increasing over the last decades in northern Patagonia coincident with an increase in summer temperatures and subtropical influence in this region. Since 1976 there has been a trend towards higher temperatures and increased drought throughout Patagonia and recent decades have seen a substantial increase in the frequency of lightning storms and lightning-ignited fires (Veblen et al., 2008; Villalba et al., 2012). Development of long-term ignition databases (e.g. satellite-derived hot-spot data) will be necessary to understand the temporal aspects (e.g. stability, trends, contingencies to extreme events, etc.) of spatial dependencies identified in this study.

5. Conclusions

Management of wildfires requires recommendations based on sound scientific principles. Fundamental to this is an analysis of the risk of fire ignitions within the study area that reveals how anthropogenic and natural factors influence ignition patterns across space, and a spatial analysis of the fine-scale autocorrelation structure of the fire ignition patterns. Here, we applied this research programme to fire ignitions in the western part of Neuquén province, Argentina. Our information theoretic approach revealed that not all hypotheses on the factors that govern the distribution of natural and human-caused ignitions received the same support, that natural and human-caused ignitions are governed by different sets of environmental drivers, and that their respective high-risk areas differed. These findings have important consequences for fire management. To contribute to this we developed a novel "two-dimensional" model of fire ignition probabilities based on separate predictions for natural and human-caused fires. This allowed the delineation of areas with fundamentally different risk types, such as areas of overall high fire risk, areas of only high natural risk, areas of only high human risk, and areas of moderate or low risk. These risk types would be glossed over in traditional "one-dimensional" models. The two-dimensional model allows fire managers to delineate target areas for consideration of major preventive treatments, strategic placement of fuel treatments, and forecasting of fire ignition. Unexpectedly, we found a strong autocorrelation of up to 35 km in the ignition patterns not explained by the broader-scale environmental variables, pointing to spatial autocorrelation in human behaviour or landscape modifications of burned areas that favour reappearance of fires. Part of this autocorrelation was explained by small-scale (<5 km) attraction of human-caused fire ignitions close to towns, however, the strength of this effect suggests that future work should investigate the causes of the observed autocorrelation in more detail. The techniques presented here can be widely applied to situations where a spatial point pattern is jointly influenced by extrinsic environmental factors and intrinsic point interactions.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2013.03.011.

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