Environmental Factors Affecting Wildfire Burned Area In South-Eastern France, 1970-2019

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Abstract.
Forest fires burn an average of about 440,000 ha each year in southern Europe. These fires cause numerous casualties and deaths and destroy houses and other infrastructures. In order to elaborate suitable fire-fighting strategies, complex interactions between human and environmental factors must be taken into account. In this study, we investigated the spatio-temporal evolution in burned area over a 50-year period (1970-2019) and its interactions with topography (Slope aspect and inclination) and Vegetation type in south-eastern France by exploiting Geographic Information System databases. Data were analyzed at two 25-year periods (1970-1994 and 1995-2019) since after 1994 a new fire suppression policy was put into place which focused on rapid extinction of fires in their early phase. In the last 25 years, burned area decreased sharply and the geographic distribution of fires also changed, especially in regions where large fires occur (Var department). Elsewhere, even though forest fires remain frequent, the total extent of the burned area decreased substantially. Fire hotspots appear closer to built-up areas in the west, randomly distributed in the east and they almost completely disappear in the central region of the study area where there is a history of large fires. Slope orientation presents an increasingly important role in the second period; S-facing slopes are preferred the most by fire N-facing slopes are preferentially avoided. Even though slope inclination is less affected by the new firefighting strategy, low slope inclinations are even more avoided after 1994. The greatest proportion of burned area is strongly associated with the location of Sclerophyllous vegetation clusters which exhibit high fire proneness and expand in area over time. Natural grasslands are also preferred by fire while Broad leaved, Coniferous and Mixed forest are increasingly avoided by fire.

1 Introduction

Forest fire is a common and important element of the earth system (Bond and Keeley, 2005) that ~~is capable of severely~~ disturbs~~ing~~ natural ecosystems and threatens human welfare and wellbeing throughout the globe. The Mediterranean climate is characterized by hot and dry summers which favor fire ignition and propagation. Consequently, wildfires are particularly active around the Mediterranean basin, and fires in the Mediterranean-climate ~~areas~~ zones are considered to have a wide range of environmental and socioeconomic impacts (Miller et al., 2009; San-Miguel-Ayanz et al., 2013; Ganteaume et al., 2013).

Forest fires burn an average of 440,000 ha each year in the Euro-Mediterranean region, and this ~~which~~ corresponds to about 85% of the total burned area (BA) in Europe (San-Miguel-Ayanz et al., 2020). Of the 5 principal Euro-Mediterranean countries concerned by forest fires (France, Greece, Italy, Portugal and Spain), France has the lowest amount of BA (San-Miguel-Ayanz et al., 2020). It also has the smallest potential burnable area since only the southern Mediterranean fringe is ~~concerned~~ affected by forest fires. France, Spain, Italy, and Greece all show similar trends in decreasing decadal BA in 1980-2010, and only Portugal ~~has~~ experienced a progressive increase during this interval (San-Miguel-Ayanz et al., 2020). It should be noted that BA ~~are~~ is generally decreasing despite increases in summer temperatures throughout the Euro-Mediterranean zone (Pokorná et al., 2018; Rodrigues et al., 2020), and this can be attributed to more efficient fire-fighting strategies (Fox et al., 2015; Turco et al., 2016; Ganteaume and Barbero, 2019).

Forest fire spatial distribution, size, and frequency are associated with several interacting factors ~~-~~that ~~are highly interactive and~~ can be categorized into two main groups: i) environmental and ii) anthropogenic. Environmental factors generally include fuel characteristics (e.g. type, water content), topography (e.g. slope inclination, altitude, aspect) and weather conditions (e.g. temperature, humidity, wind speed); anthropogenic factors include the characteristics of the transitional zone between wildland vegetation and artificial areas in the Wildland Urban Interface (WUI).

Among the environmental characteristics, several studies provide evidence of spatial patterns relating forest fire probability and BA to topography ~~to forest fire probability~~ (Dickson et al., 2006; Nunes et al., 2016; Padilla and Vega-García, 2011) ~~and burnt area~~. Slope aspect affects incoming solar radiation and can determine ~~the~~ fuel type, fuel moisture, and fuel density which all influence flammability (Holden et al., 2009). In addition, aspect influences the degree of ecological change related to fire (fire severity) (Birch et al., 2015; Estes et al., 2017; Parks et al., 2018). In the northern hemisphere, south-facing slopes receive more solar radiation during the day than north-facing slopes, and this can enhance burn severity (Alexander et al., 2006; Oliveira et al., 2014a; Oliveras et al., 2009) but the trend is not systematic (Broncano and Retana, 2004). In addition to the impact on fire severity, other studies (Mouillot et al., 2003) have demonstrated that south-facing slopes in Corsica (France) can burn more frequently than other exposures. On the n~~N~~orth shore of the Mediterranean, s~~S~~outh-facing slopes frequently have more housing than north-facing slopes, and this may contribute to a greater number of ignitions (Fox et al., 2018). Steep slopes tend to have higher spread rates ~~of spread~~ and fire intensities~~y~~ (Capra et al., 2018);~~,~~ ~~as well as increased~~ fatality rates are also greater compared to ~~-over~~ flat areas (Molina-Terrén et al., 2019). Csontos and Cseresnyés (2015) observed an exponential increase in upslope fire spread with ~~the~~ increase in slope inclination whereas downslope fire spread velocity was unaffected by slope angle and was similar to rates detected on flat terrain. Slope and altitude tend to be correlated but their association with fires is often conflicting. For instance, Nunes et al., (2016) ~~studied~~ found that BA and ignition density ~~on a municipal scale in Portugal and found both are~~ were positively ~~affected~~ correlated with~~by~~ elevation and slope at a municipal scale in Portugal. Similarly, ~~in~~ Elia et al., (2019) ~~results~~ showed that the probability of fire ignition increased with elevation and slope in southern Italy. However, ~~other studies such as~~ Narayanaraj and Wimberly, (2012) observed ~~that~~ a negative impact of elevation and slope inclination ~~had a negative association with~~ on human-caused fires.

The role of vegetation is complex and can be influenced by flammability (Michelaki et al., 2020; Molina et al., 2017) or spatial patterns of vegetation in the landscape (Curt et al., 2013). Vegetation continuity affects fire propagation which contributes to determine BA (Duane et al., 2015; Fernandes et al., 2016). Vegetation type is another important factor to consider which has explored in number of studies though fire selectivity indices (Bajocco and Ricotta, 2008; Barros and Pereira, 2014; Carmo et al., 2011; Moreira et al., 2009; Moreno et al., 2011; Nunes et al., 2005; Pereira et al., 2014). Overall, there is ~~a~~ widespread agreement in literature that shrublands are regarded as fire prone areas at multiple scales: regional (Carmo et al., 2011; Moreno et al., 2011), national (Nunes et al., 2016, 2005) and continental (Moreira et al., 2011; Oliveira et al., 2014b; Pereira et al., 2014) scales.The probability of large fires is greater in dense shrublands than in forested ecosystems in the Mediterranean basin (Moreira et al., 2011; Ruffault and Mouillot, 2017). According to Mermoz et al., (2005), fire proneness of shrublands could be related to their recovery rate since shrublands can regenerate faster and favor fuel accumulation in a short time unlike forests which take longer to recover and ~~spread~~expand. In addition, Oehler et al., (2012) point out that shrubs are considered ~~as~~ a low suppressing priority by fire fighters due to the low cost of ~~its~~ restoration. In Europe, ~~Other vegetation types, such as~~ grasslands~~,~~ are also considered to be fire prone ~~in Europe~~ (Oliveira et al., 2014a). Cultivated areas are the least fire prone vegetation types ~~mainly~~ because of their low combustibility and ~~their geographic~~ proximity to built-up land covers which facilitates rapid fire detection and suppression (Moreira et al., 2011). Forested areas are found to be more fire prone than cultivated areas but less than shrublands (Moreira et al., 2011). More specifically, broad-leaved forests are usually less prone to burning than coniferous species which present a greater fire hazard (Moreira et al., 2009; Oliveira et al., 2014a).

Spatial relationships between fire occurrence and environmental factors evolve over time due to changes in ~~Several of the aforementioned factors do not remain constant in the spatial and temporal domain and thus determining the relative influence of changes in~~ biomes~~,~~ and climate, but also as the result of ~~in~~ fire management practices. Mapping and understanding these trends are ~~is~~ crucial ~~both~~ for evaluating the effectiveness of fire-fighting strategies and developing suitable policies~~y-making and fire management~~ (Bowman et al., 2017). There are numerous recent efforts that aim to analyze spatial and temporal trends of fire activity at a global, national and regional level. Otón et al., (2021) analyzed global trends of BA based on the FireCCILT11 database which is the longest available global BA dataset to date (1982-2018). At a national level Catarino et al., (2020) investigated the trends of annual BA in Angola between 2001 and 2019 using MODIS products (MCD64A1) and associated the significant trends to land cover, ecological regions and protected areas. Ganteaume and Barbero, (2019) utilized a long-term (1957-2017) fire geodatabase to analyze spatio-temporal variations of large fires in terms of frequency and BA, in the French Mediterranean. Silva et al., (2019) used a satellite derived BA dataset covering a 39-year period over the Iberian Peninsula to study BA trends and explore the relationship between areas with significant BA trends and fire danger. Urbieta et al., (2019) studied the spatio-temporal trends in Spain between 1980 to 2013 with regard to fire frequency, BA and fire size, and their relationship with changes in climate, land-use and land-cover, and fire suppression. Viedma et al., (2018) assessed the changing role of environmental and human-related factors in reference to fire activity, in west-central Spain from 1979 to

2008. Fire suppression is an important factor that can influence fire spread. In France, as a response to the large fires that occurred between 1986 to 1990 a major change in fire suppression strategy was established in the 1990s; it focused on rapid suppression of fire ignitions regardless of the weather conditions in order to avoid fire propagation (Direction de la Sécurité Civile, 1994). The fire policy had a significant impact in fire activity in ~~fire-prone areas like in~~ Southern France and weakened the fire-weather relationship (Ruffault and Mouillot, 2015). Despite the sharp decrease in BA after the full implementation of the fire management policy, its ~~efficiency~~ effectiveness on very large fires ~~is~~ was not as successful as for smaller fires~~,~~ since changes in BA that correspond to large return periods ~~don't seem~~are not significant (Evin et al., 2018). Although many studies have focused on determining relationships between fire behavior and driving factors (Mhawej et al., 2015), ~~and the relative level of importance of factors can vary from one region to another depending on the environmental and socioeconomic contexts and the scale of a study (Moritz et al., 2005; Lafortezza et al., 2013; Ganteaume and Long-Fournel, 2015). F~~few studies have examined how ~~efficient~~ fire suppression strategies impact the spatial distribution of BA. Identifying spatial patterns and the main driving forces that determine fire distribution provides useful information for fire and civil protection agencies, and it assists in allocating appropriate firefighting resources and in designing proper prevention actions~~, especially in the Mediterranean area~~ (Moreira et al., 2011).

The objective of this study is to quantify changes in spatio-temporal BA ~~spatial and temporal~~ patterns induced by a major shift in fire suppression strategy ~~that was~~ initiated in the early 1990s in South-eastern France. The time interval under study spans 5 decades (1970-2019) and includes the relation of BA with respect to environmental factors such as a) topography (S~~s~~lope aspect and inclination~~, slope orientation~~) and b) ~~v~~Vegetation type. Although several studies have investigated the relationships between BA and environmental factors, very few have covered such a long-time interval based on burn scar polygons, nor have they been explicitly related to changes in fire suppression methods.

Field Code Changed

2 Data and Methods

2.1 Study area

The study area is comprised of a subset of the 3 administrative departments with the greatest BA in continental France (only Corsica has greater burned area) according to the French official forest fire database ~~database for forest fires in the French Mediterranean area~~ (promethee.com): Bouches-du-Rhône, Var, and Alpes-Maritimes (Table 1, Fig. 1). ~~The a~~Areas within the departmental limits that were excluded~~,~~ represent surfaces that cannot burn such as~~: i)~~ marshlands in the westernmost part of Bouches-du-Rhône and ~~ii)~~ high alpine mineral surfaces located in the northern part of Alpes-Maritimes.

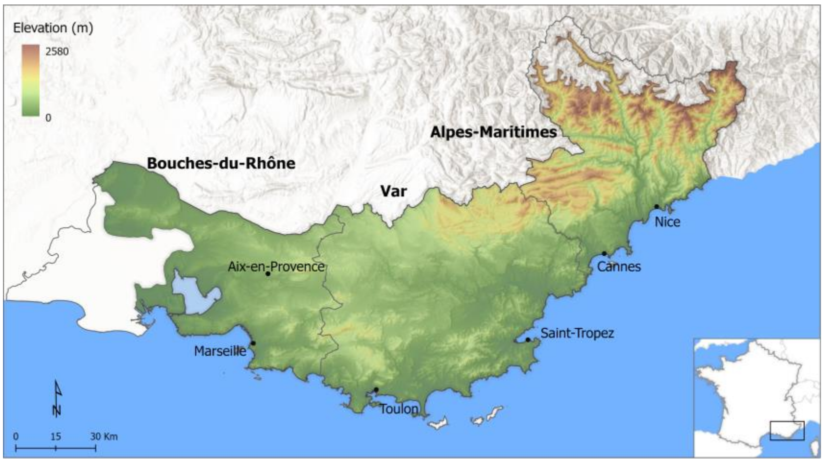

Figure 1: Map of south-eastern France showing the study area and the departmental limits overlaid on a 5 m Digital Elevation Model.

Table 1: Environmental characteristics of the study area per departmental unit

	Bouches-du-Rhône	**Var**	**Alpes-Maritimes**
Total area (km²)	3456	6019	3495
Forested area (km²)	1530	4044	2727
Ratio forest/total (km²)	0.44	0.67	0.78
Mean slope (°)	8.8	11.9	24.3
Median slope (°)	5.7	9.6	25.2

Topography varies ~~noticeably~~ from west to east (Fig. 1). The gentlest slopes are found in the west (Bouches-du-Rhône) and both altitude and slope inclination increase ~~towards the east~~ eastwards. The steepest slope inclinations are found in the northeastern part of the study area where the French Alps are located. Topography influences population distribution since much of the built area is concentrated along the coast or on shallow to intermediate slopes in the WUI. In the Bouches-du-Rhône, the western portion of the department has particularly low population densities due to the presence of the national park and wetlands mentioned above. Similarly, much of the population in the Alpes-Maritimes is concentrated in the southern portion of the department. The 2010 population densities of 388.8, 167.5, and 252.0 persons/km² for the Bouches-du-Rhône, Var, and Alpes-Maritimes, respectively, are approximative ~~therefore only gross approximations~~ as they simply divide population by total area without accounting for geographic distributions. The order, however, is accurate and shows the greatest population density for Bouche-du-Rhône, and the lowest for the Var. Based on the demographic and environmental characteristics described above, the westernmost section (Bouche-du-Rhône) of the study area has low potential for fire ignition and propagation but increases when moving towards the eastern half of department. The central part of the study area (Var department) has a high potential for fire ignition and the greatest potential for fire propagation since it has a high forested area and a large continuous WUI area. Finally, the eastern section (Alpes-Maritimes department) has high ignition and propagation potentials in the southern portion of the department and low ignition / high propagation at higher altitudes.

2.2 Fire database

Forest fire research in France is ~~usually~~ frequently based on the national database for forest fires in France (www.promethee.com) where fire location is ~~described~~ defined as~~by~~ the municipality where fire ignition occurred. For this study, we used a fire Geographic Information Systems (GIS) database provided by the National Forestry Office (Office National des Forêts, ONF) and the Delegation for the Protection of the Mediterranean Forest (Délégation à la Protection de la Forêt Méditerranéenne, DPFM). Even though the number of recorded fires is significantly lower than the Promethee database, the total area burned ~~in a given time~~ is almost identical; very small fires recorded in Promethee are not all digitized in the ONF database~~.~~ To the best of our knowledge, this is only the second ~~exploitation~~ use of this geodatabase after Ganteaume and Barbero (2019). The dataset includes more than 3,000 digitized burn scar polygons for fires that occurred between 1970 and 2019. Due to the long temporal extent of the database, the accuracy and the methods used to define burn scars varied over time. In the 1970s, burn scars were mapped using field measurements with GPS devices, and the technique progressively evolved to integrate remote sensing data (satellite imagery, orthophotos). Although the description of how BA was defined is not recorded in the database, earlier polygons are clearly less accurate (coarse shapes with little detail) than burn scars after the advent of satellite imagery (Fig. 2).

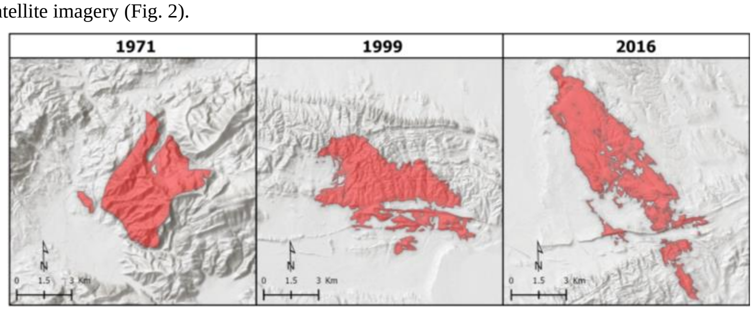

Figure 2: Evolution of digitized burn scar accuracy over the past decades.

2.3 Environmental variables

2.3.1 Topography

Burn scar polygons were rasterized to a 5 m spatial resolution and overlain on a 5 m Digital Elevation Model (DEM) extracted from RGE-ALTI©, the official National Geographic Institute (Institut Géographique National, IGN) database. The DEM was used to calculate Slope aspect and ~~slope~~ inclination. In the conversion of vector polygons to raster cells, BA polygons smaller than half the cell size (25 m²) were not defined as burned during rasterization, so BA for the Slope aspect and ~~slope~~ inclination analyses represent approximately 96 % of actual BA in the study area. Aspect was divided into 5 categories: F~~f~~lat, N~~n~~orth, E~~e~~ast, ~~s~~South and ~~w~~West. ~~Slope~~ Inclination was divided into 5 categories: 0°-10°, 10°-20°, 20°-30°, 30°-40° and>40°.

2.3.2 Vegetation type

For the computation of the forested BA and the identification of fire-prone vegetation categories, GIS forest layers were extracted from the European CORINE land cover (CLC) database. The database includes five reference years 1990, 2000, 2006, 2012 and 2018. In addition to the CLC reference layers, it was considered best to back~~-~~cast two additional forest cover layers for 1972 and 1980 to account for any transitions between forested and non-forested surfaces for the two decades preceding the CLC database. The methodology followed for the projection process is addressed in Subsection 2.5.1. The fire geodatabase was then matched with the CLC layer that was chronologically closest to the equivalent fire period (see Table 2).

Table 2: Corine land cover layers and their respective fire periods.

Corine Land Cover	Fire period
1972 (~~Projected~~Predicted)	1970 – 1974
1980 (~~Projected~~Predicted)	1975 – 1984
1990	1985 – 1994
2000	1995 – 2002
2006	2003 – 2009
2012	2010 – 2014
2018	2015 – 2019

The vegetation types that were used in the current study follow the CLC nomenclature: Broad-leaved forest, Coniferous forest, Mixed forest, Natural grasslands and Sclerophyllous vegetation (Fig. 3). Although Natural grasslands and Sclerophyllous vegetation are not forests, the categories will be referred to collectively as wildland or forested areas indiscriminately for the sake of brevity.

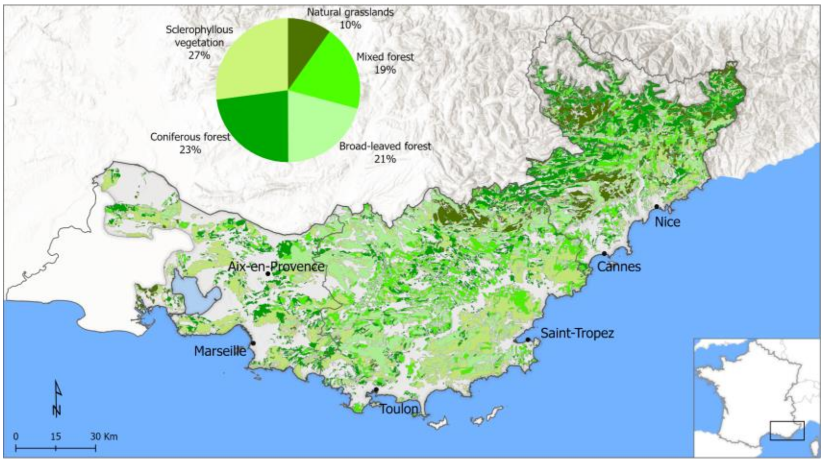

Figure 3: Distribution of vegetation types based on CLC 2018.

2.3.2.1 Forest layer projection

Although most urban growth occurred on agricultural land (Roy et al., 2015) and forest cover changed little, the Land Change Modeler (LCM) module of Terrset (Eastman 2020) was used to predict vegetation cover in 1972 and 1980. LCM is programmed to forecast change from an earlier to a later date, so going back in time (backcast) required the temporal inversion of filenames for the 1990 (renamed to 2000) and 2000 (renamed to 1990) CLC layers; in this way, land cover was simulated for 1980 and 1972. Land cover categories were simplified from the original CLC categories to the following: Built, Broad-leaved forest (Broad), Coniferous forest (Conifer), Mixed forest, Natural grasslands (Grass), Sclerophyllous vegetation (Bush), other, and water. Only transitions greater than 0.05 % of the landscape (14.3 km²) were modeled, and these included the following (From-To): Bush-Grass, Bush-Other, Built-Other, Grass-Other, Broad-Bush, Other-Grass, Bush-Conifer, Other-Bush, Bush-Broad, Bush-Mixed, Mixed-Bush, Other-Conifer, Mixed-Broad, Mixed-Other, Other-Broad, Other-Mixed, Broad-Other, Grass-Bush, Mixed-Conifer, Built-Mixed, Built-Bush, Conifer-Mixed. Note that these are the inverse of historical trends, so the Built-Mixed transition actually backcasts the historical transition of Mixed forest to Built area. Explanatory variables used to predict land cover change were the following: Altitude, Slope inclination, Distance from Built area, Distance from Broad, Distance from Conifer, Distance from Mixed, Distance from Grass, Distance from Bush, Distance from Other and Distance from water. According to Eastman (2020), Cramer's V values of ≥0.15 for explanatory variables are useful and should be kept in the model, and all explanatory variables used here met this criterion. Accuracy rates to model transitions ranged from 65 % to 90 % with mean and median values of 78 % and 80 %, respectively.

2.4 Fire history 1970-2019

A 500x500 m grid (25 ha) was created and overlaid on the study area in order to measure the percentage of ~~-~~each cell that was burned each year between 1970 and 2019 (50 years) (Fig. 4). These percentage values were then summed to produce the cumulative percentage of BA for each cell. This approach facilitated the effort to identify clusters of cells/areas that have been burned multiple times ~~through time but also~~ and to give an overview of the spatial distribution of BA in the region. To better illustrate the impact of suppression strategies on fire occurrence, the ~~aforementioned~~ method~~ology~~ was applied to two 25-year subsets of the fire dataset i) 1970-1994, and ii) 1995-2019 as the mid-point break corresponds ~~roughly~~ to the major shift in firefighting strategy and allocated resources in France.

~~the spatial and temporal trends in the study area, the aforementioned methodology was applied to two 25-year subsets of the fire dataset ... 9. The distinction between the earlier and later intervals was defined to highlight the impact ... occurrence as the break corresponds roughly to a major shift in firefighting strategy and allocat... F...~~

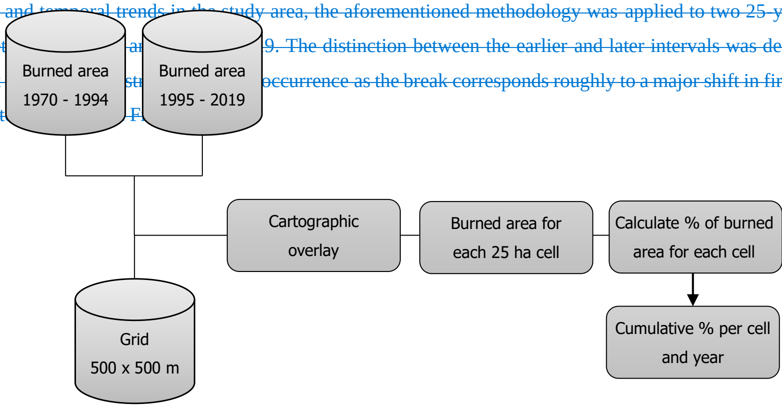

Figure 4: Flow chart depicting the processing steps to generate the cumulative percentage of forested burned area per cell.

2.5 Spatio-temporal analysis – Contextual Mann-Kendall

In order to identify spatio-temporal trends within the entire time period (1970-2019), a modified version of the Mann-Kendall test was applied (Kendall 1975; Mann, 1945). The Mann-Kendal test is a non-parametric test which is used to statistically assess monotonic upward or downward trends for a variable through time. In this study we used the contextual Mann-Kendall (CMK) test which was introduced by Neeti and Eastman (2011), and it differs from the original ~~one since it~~ test by evaluat~~es~~ing trends at a 3x3 cell neighbourhood for each cell in a grid. The ~~CMK method~~specific method has been used to assess trends in BA with satisfactory outcomes (Silva et al., 2019; Catarino et al., 2020; Otón et al., 2021).

The CMK method was devised from ~~established on~~ Tobler's First Law of Geography (Tobler, 1970) which states that "everything is related to everything else, but near things are more related than distant things." By assuming that trends show signs of spatial autocorrelation between adjacent cells, the ~~method~~ CMK test allows for greater confidence in identifying the presence of a trend (Neeti and Eastman, 2011). However, ~~the test~~ it requires observations to be a set of independent random variables and thus applying the test on data that are temporally autocorrelated may lead to false rejection of the null hypothesis of no trend (Douglas et al., 2000). To assess the temporal autocorrelation in our dataset we applied the Durbin-Watson test (Durbin and Watson, 1950), and to remove it, the prewhitening procedure by Wang and Swail~~,~~ (Wang and Swail, 2001) which preserves the same temporal trend but without the ~~temporal~~ autocorrelation (Fig. 5).

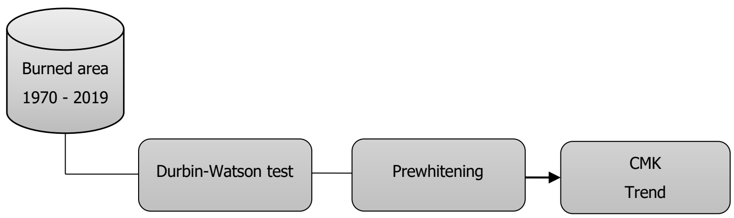

Figure 5: Flow chart depicting the processing steps to estimate trend significance using the Contextual Mann-Kendall method.

2.6 Fire Selectivity (Jacob's Index)

In order to examine the fire proneness of the environmental variables considered in this study (~~s~~Slope~~, aspect~~ aspect and inclination, ~~and~~ V~~v~~egetation type) ~~between the two 25-year periods we calculated~~ a resource selection index was calculated for each 25-year interval. ~~Even though r~~Resource selection is based primarily on wildlife ecology (Manly et al., 2002), but its use has been extended to include ~~there are several studies that applied similar methods for~~ fire selectivity (Bajocco and Ricotta, 2008; Barros and Pereira, 2014; Moreira et al., 2001, 2009; Moreno et al., 2011; Nunes et al., 2005; Oliveira et al., 2014a). The rationale behind fire selectivity is that fires burn~~s~~ selectively when the proportion of a class (e.g. ~~a~~ type of vegetation) within a burned area is higher than the proportion of the available area to burn. The opposite applies ~~If~~ when a specific class of variable is burned proportionally less than the ~~proportion available within an area~~available area (fire avoidance).
In our work, we used Jacob's selectivity index (Jacobs, 1974) which is defined as:

$$D_i = \frac{r - p}{r + p - 2rp} \quad (1)$$

r stands for the proportion of a resource class ***i*** used by fire, and ***p*** is the proportion of a resource class ***i*** available to fire. Jacobs' index values range between -1 and 1. Positive values indicate fire preference, ~~while the~~ negative ~~ones~~ values indicate fire avoidance. The index was calculated for each class of the environmental factors (described in the subsequent sections) for each year. Similar to other studies (Barros and Pereira, 2014; Nunes et al., 2005), the available area for each fire to burn is defined as twice the amount of area burned by each fire. (Fig. 6).

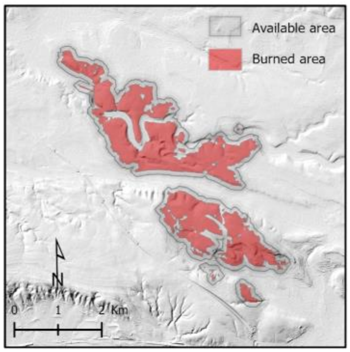

Figure 6: Illustration of burned area (*r*) and available area (*p*) to be used by a fire. The available area (the sum of the burned area + buffer zone) around each fire corresponds to twice the burned area.

2.7 Geographically weighted regression

~~To evaluate the importance of the environmental factors affecting BA and to observe whether their importance was impacted by the shift in fire suppression,~~ a ~~g~~Geographically weighted regression (GWR) was used to quantify the impact of the change in firefighting strategy on the relative importance of the environmental factors. ~~Applications of~~ GWR is applied ~~can be found~~ in ~~variety~~ wide range of interdisciplinary fields including forest fires (Koutsias et al., 2010; Martínez-Fernández et al., 2013; Nunes et al., 2016; Rodrigues et al., 2016; Kolanek and Szymanowski, 2021). GWR is a local non-parametric regression method (Fotheringham et al., 2003) that allows the relationships between dependent and explanatory variables to vary over space. The basic form of a GWR model, provided by Fotheringham et al. (1998, 2003) is defined as:

$$y_{i=\beta_{io}} + \sum_{z=1}^{j} \beta_{iz}\, x_{iz} + \varepsilon_i \quad (2)$$

Where y_i is the dependent variable at location *i*, β_{i0} is the intercept parameter at location *i*, *j* is the number of explanatory variables, b_{iz} is the local regression coefficient for the *z*th explanatory variable at location *i*, x_{iz} represents the *z*th explanatory variable at location *i* and ε_i denotes the random error at location *i*. Since GWR allows coefficients to be spatially heterogeneous, a sub-model for the location of each observation is created that considers only a subsample of the total observations, where observations in closer proximity have ~~higher~~ a greater effect in determining the local set of coefficients than observations located ~~in larger~~ at further distances (Fotheringham et al. 1998). This neighbourhood is called a "kernel,"~~,~~ ~~while~~ and the maximum distance from a regression point at a location *i* is defined as "bandwidth". The bandwidth is an important parameter than can be defined in two different ways: i) fixed bandwidth, (fixed distance for each regression point) and ii) adaptive bandwidth (fixed number of nearest neighbours for each regression point). The first type of neighbourhood is more appropriate when data are regularly distributed across apace whereas the second type is more appropriate for data that form spatial clusters. In the current work the adaptive bandwidth approach was utilized to fit the GWR model which was optimized based on the value of Akaike Information Criterion (Akaike, 1998). For each of the 3 environmental variables ~~mentioned in subsection 2.3.1 and 2.3.2~~described above, a univariate GWR model was used to explore the relationship with the dependant variable (% of BA) for the two 25-year periods i)1970-1994 and ii)1995-2019.

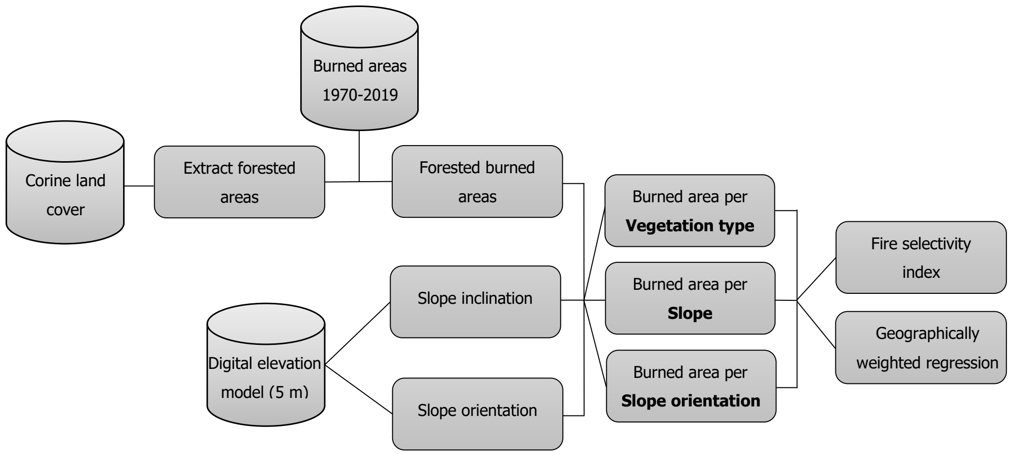

Figure 6~~7~~: Flow chart depicting the processing steps and data used to relate BA to Vegetation type, Slope inclination and orientation.

3. Results

Results presented below will first describe fire history for the entire time~~1970-2019~~ interval (1970-2019) and then analyze the spatio-temporal evolution of BA split according to the two 25-year periods. Finally, it will explore the relationship of BA to topography (~~s~~Slope ~~orientation~~ aspect and inclination) and V~~v~~egetation type. Factor-specific results will be discussed as they are presented in the following results sections while broader considerations will be explained in the Discussion section.

3.1 Fire history ~~1970-2019~~

In total, 3,382 fires burned 296,820 ha in 1970-2019. The mean and median areas of BA are 87.7 ha and 4.2 ha, respectively; these values reflect the typical ~~highly negatively~~ positively skewed distribution~~s~~ of fire size where the vast majority of fires are small and a few fires, accounting for most of the burned area, are very large. The number of fires equal to or greater than 100 ha, 500 ha, and 1,000 ha is 378 (11.2%), 123 (3.6 %) and 65 (1.9 %), respectively. Of the total number of fires, 2,424 (88.2 %) occurred in forested landscapes, and these burned an area of 263,645 ha (88.8 % of total BA). Mean and median values for forested landscape fires ~~area~~ are slightly greater than for all fires at 111.7 ha and 6.5 ha, respectively. The number of fires equal to or greater than 100 ha, 500 ha, and 1,000 ha is 314 (13.0 %), 106 (4.4 %), and 60

(2.5 %), respectively. As stated above, results presented below will deal exclusively with the forested BA that was occupied by one of the vegetation types mentioned in section 2.3.2 since the trends with respect to vegetation and topography for all fires and forested landscapes are nearly identical.

Annual forested BA varies significantly from year to year (Fig. 8) although there are clear differences between the first two decades (1970-1990) and the last three (1991-2019). The mean and median annual BA are 5156.4 ha and 2746.1 ha, respectively. ~~Most of the~~ Several big fires occurred in the 1980s followed by a sharp decrease in the early 1990s. Similarly to the rest of ~~the~~ southern Mediterranean Europe, ~~the majority~~most of the forested BA is related to a small number of large fires (Turco et al., 2016). Only 5 years (1979, 1986, 1989, 1990 and 2003) of the 50-year record account for almost half of the total forested BA (126,700 ha). The forested BA for each of these years surpasses 20,000 ha, attaining nearly 36,000 ha in 1989. Of the 5 years cited above, only 2003 is found in the second 25-year interval. As described by Fox et al., (2015) for the Alpes-Maritimes, ~~this~~ the decrease in BA corresponds to an improvement in fire-fighting strategy since the latter period had some of the hottest summers on record; ~~, and~~ the same explanation appears to hold for the neighboring departments studied here.

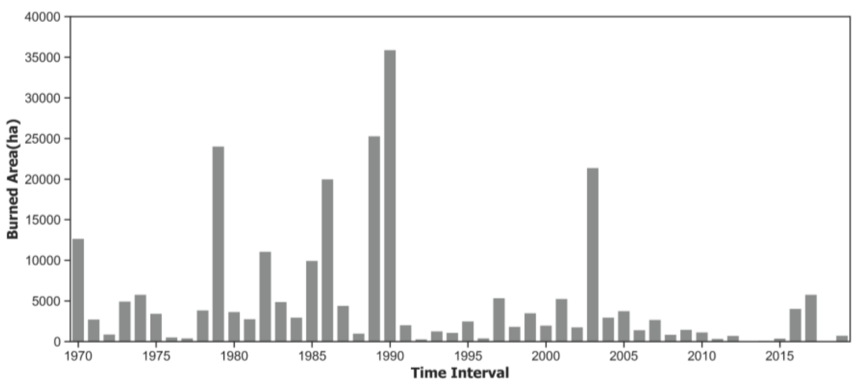

Figure 7~~8~~: History of annual forested burned area and number of fires from 1970 to 2019.

Figure 9 maps cumulative percentage area burned inside each 25 ha cell for 1970-1994 and 1995-2019, respectively. Generally, most fires occur in the WUI north of the large coastal cities since densely developed areas have too little vegetation to burn and relatively remote areas have too few ignition sources. Although we did not treat wind direction or speed, BA shapes in both periods tend to align themselves with known wind patterns in the region: they have a NW-SE orientation throughout most of the western and central sections (Bouches-du-Rhône and Var departments) but show little preferential orientation in the eastern department of Alpes-Maritimes where wind speeds are lower than the “Mistral” winds in the Rhône valley. There is a clear difference between the two periods with the second one having significantly fewer burned cells, which are also slightly more spatially dispersed. In addition, cumulative percentage values are noticeably lower with a small number of cells (302) exceeding 100 % and very few (9) reaching 200 %. All major hotspots disappear in the second interval apart from some located mainly in the western area of study zone near Aix-Marseille.

The largest patches in both intervals are found in the central part of the study zone in the Var department which combines continuous forest cover and a lower population density that is distributed more evenly throughout the department. The two largest continuous BA clusters are found here, one north of Saint-Tropez and one east of Toulon. In the 1995-2019 time interval, the first cluster shrunk whereas the second one completely disappeared. In the western section of the study area (Bouches-du-Rhône), burned patches are located in constrained areas between densely built zones (Aix-en-Provence and Marseille) with several cells displaying high fire recurrence. In the eastern section of the study area (Alpes-Maritimes), where population is particularly dense along the coast (Cannes-Nice), BA cells are concentrated inland along the periphery of the coastal built-up area. A major hotspot with the highest cumulative percentage burned area is found just west of Cannes, and this patch almost disappears in the second period. In comparison to the rest of the study area, patches in the eastern department of the Alpes-Maritimes are smaller and more numerous with high to very high recurrence, even at higher altitudes.

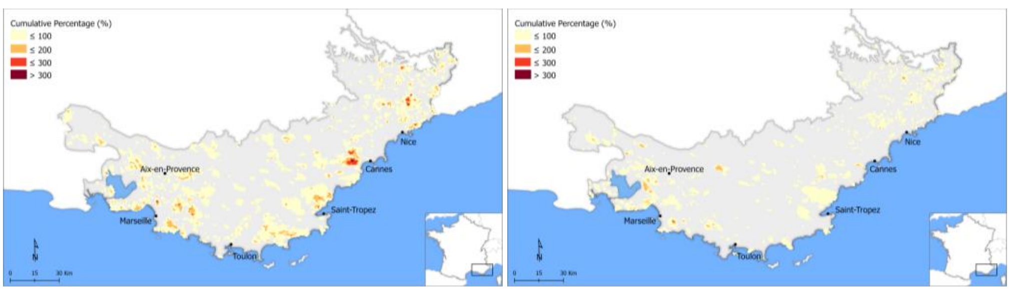

Figure 8~~9~~: Cumulative percentage of forested burned areas in the 1970-1994 interval (left) and in the 1995-2019 interval (right) over a 500 x 500 m grid.

3.1.1 Spatio-temporal analysis

Results of the CMK method depict areas of increasing and decreasing trends in terms of mean annual BA over the study area (Fig. 10). Positive Z-scores (colored in red) correspond to areas with increasing trends and negative Z-scores (colored in blue) correspond to areas with decreasing trends. Overall, a general decreasing trend of BA throughout most of the study area can be observed, with approximately 60% of the cells corresponding to a negative value. The largest clusters of negative Z-scores are located predominately in the central areas of the region, north of Toulon, north of Saint-Tropez, and west of Cannes, with small negative patches north-east of Marseille and north of Nice. ~~like W of Cannes (major hotspot that disappears in the second period), N of Saint-Tropez, N of Toulon and NE of Marseille)~~. ~~Clusters of p~~Positive Z-scores~~s~~ clusters are ~~much~~ more constrained in terms of size and are generally dispersed. Significant decreasing trends are relatively limited and can be spotted in areas such as east of Marseille, west of Cannes and north of Nice. ~~like N of Nice, W of Cannes and E of Marseille~~. ~~On the contrary, s~~Significant positive trends are detected in several locations (although limited in area) such as between Aix-en-

Provence and Marseille and in the northeastern part (Alpes-Maritimes department) of the study area. ~~Zones near the biggest cities in the region (Nice, Marseille and Aix-en-Provence)~~ Although contrasting negative-positive trends co-exist in close proximity near Marseille and Aix-en-Provence, the greatest speckled pattern is found in the Alpes-Maritimes department where fires are smaller and more randomly distributed~~, present a contrasting pattern of mixed increasing/decreasing trends often at very short distances from one another~~.

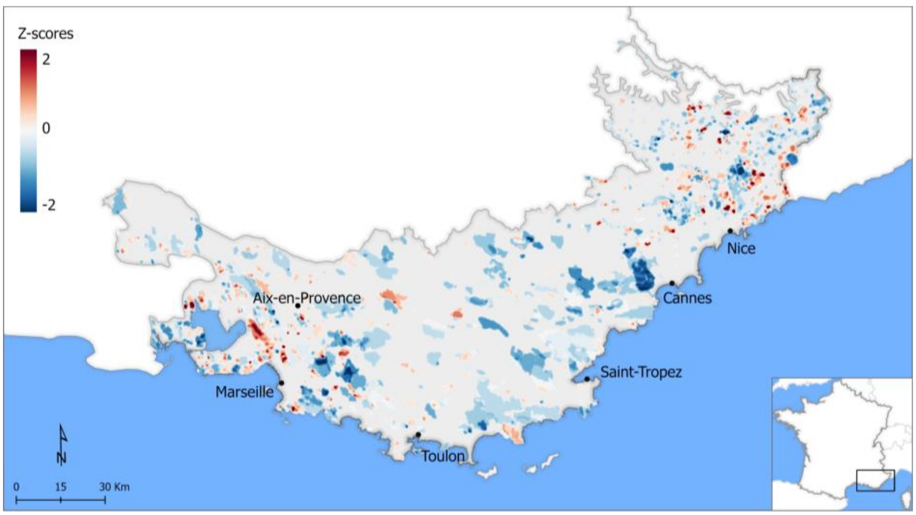

Figure 9~~10~~: Trends of mean annual burned area between 1970 to 2019 based on the Contextual Mann-Kendall method. Areas with positive Z-scores depict increasing trends of burned area, while negative Z-scores show decreasing trends.

3.2 Fire selectivity and Topography

Topographic effects studied here include ~~both~~ Slope aspect and ~~slope~~ inclination. Since some areas may have greater BA values simply because in a given topographic class is more frequent in the landscape, Jacob's selectivity index was calculated in order to identify potential classes of ~~slope~~ aspect~~s~~ and ~~slope~~ inclination~~s~~ that are preferred by fire between two periods: i) 1970-1994 and ii) 1995-2019.

~~3.2.1 Slope aspect~~

Figure 11 shows fire preference (Jacobs' index >0) and fire avoidance (Jacobs' index <0) for the two 25-year periods under study. Between 1970-1994, S-facing slopes have a weak positive median value (0.02) while the others are all negative. Values become increasingly negative in the following order: W (-0.08), E (-0.12), N (-0.18) and flat (-0.38). In the second period (1995-2019), the median fire selectivity of S-facing slopes (0.1) increases and presents a clear difference with other trends which either remain the same (flat) or decrease. N-facing (-0.33) slopes in particular appear to be even less prone to fire in the 1995-2019 interval, and flat surfaces continue to show the greatest aversion to fire.

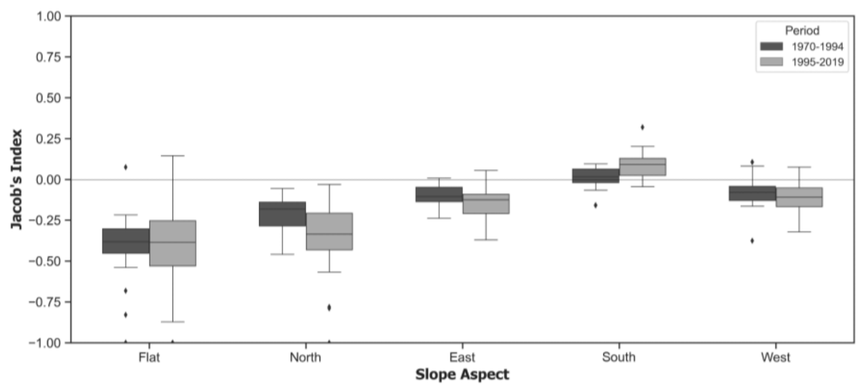

Figure 10~~11~~: Boxplot representing the distribution of Jacobs' index (ranging from -1 to +1) for 1970-1994 (left) and 1995-2019 (right) according to Slope aspect. i) Median value (50th percentile): bar within the box, ii) first quartile (25th percentile): bottom part of the box, iii) third quartile (75th percentile): top part of the box. Whiskers represent observations outside the middle 50% and points represent outliers.

~~3.2.2 Slope inclination~~

As for aspect, figure 12 shows fire selectivity for each of the two periods based on Jacobs' selectivity index according to Slope inclination. Overall, fire is not selective with regards to inclination; in the first period, the gentlest (≤10°) and steepest (>40°) inclination categories tend to be avoided by fire (values of -0.20 and -0.19, respectively). In the second period, median fire selectivity for gentlest slopes (≤10°) show slightly stronger avoidance, shifting from -0.2 to -0.29 while ~~S~~steepest (>40°) slopes, located mainly in the eastern segment of the study area, exhibit a similar change, shifting from -0.19 to -0.27. Intermediate slope categories (10°-40°), which account for a high percentage of BA in the western (Bouches-du-Rhône) and central (Var) study area, do not exhibit any clear fire selectivity pattern.

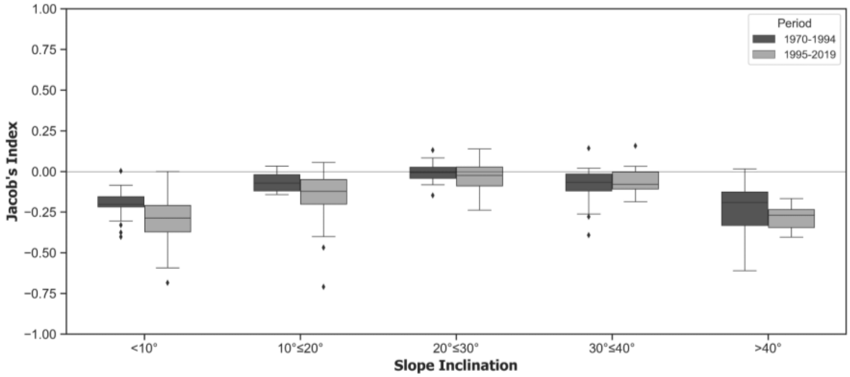

Figure 11~~12~~: Boxplot representing the distribution of Jacobs' index (ranging from -1 to +1) for 1970-1994 (left) and 1995-2019 (right) according to slope inclination. i) Median value (50th percentile): bar within the box, ii) first quartile (25th percentile): bottom part of the box, iii) third quartile (75th percentile): top part of the box. Whiskers represent observations outside the middle 50% and points represent outliers.

3.3 Fire selectivity and Vegetation type

Forested and semi natural vegetation is distributed between 5 categories, of which Natural grasslands and Sclerophyllous vegetation have the lowest and the highest 50-year average covers, respectively, as the following values show: Broad-leaved forest (~~–~~20.6 %)~~;~~, Coniferous forest~~,~~(24.1 %)~~:~~, Mixed forest~~,~~ (19.2 %)~~,~~; Natural grasslands~~,~~ (11.2 %), and Sclerophyllous vegetation~~,~~ (24.9 %). ~~Through the last 5 decades~~Over the 50-year study period, Mixed and Broad-leaved forest ~~remained~~maintain roughly the same area~~ roughly the same in terms of coverage,~~ whereas Conifers present a slight but decreasing trend. Sclerophyllous vegetation expanded in the study area (≈6 % increase), becoming the most common type in the last 3 decades. Finally, N~~n~~atural grasslands is by far the least common type and shrunk slightly (≈3,5 % decrease) over ~~the course of the last 50 years~~time.

Table 3 Average and relative forested areas according to vegetation type between 1970 to 2019.

Type	Area (ha)	%
Broad-leaved forest	172,547	20.6
Coniferous forest	201,262	24.1
Mixed forest	160,973	19.2
Natural grassland	93,322	11.2
Sclerophyllous vegetation	208,057	24.9
Total	836,161	

Fire selectivity with regards to V~~v~~egetation type is presented in figure 13. ~~-~~In the first period, 3 types of vegetation show signs of fire avoidance: ~~m~~Mixed ~~forest~~ (-0.28), ~~b~~Broad-~~-~~leaved ~~forest~~ (-0.24) and ~~c~~Coniferous ~~forest~~ (-0.21). ~~, whereas n~~Natural grasslands and ~~s~~Sclerophyllous vegetation display weak preference by fire with median values of 0.09 and 0.05, respectively. Even though the order changes slightly in the second period, the effects of the fire suppression strategy on vegetation types are more evident than for the topographic factors. On the one hand, all three forest types are more clearly avoided by fire while ~~O~~on the other hand, N~~n~~atural grasslands and ~~s~~Sclerophyllous vegetation show even stronger fire preference in the second period shifting from 0.08 to 0.28 and from 0.05 to 0.15, respectively.

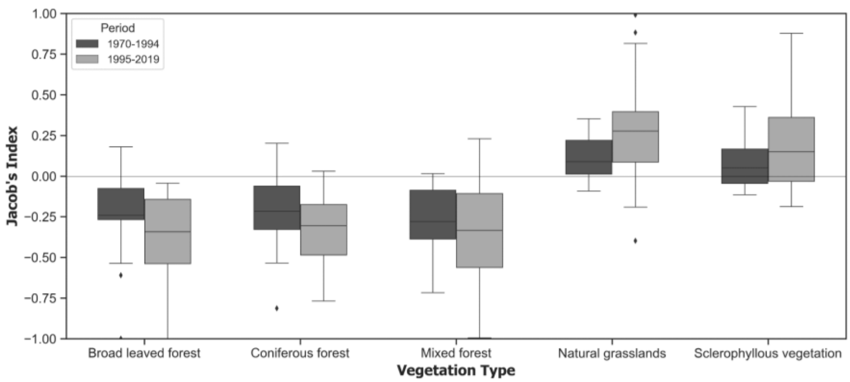

Figure 12~~13~~: Boxplot representing the distribution of Jacobs' index (ranging from -1 to +1) for 1970-1994 (left) and 1995-2019 (right) according to vegetation type. i) Median value (50th percentile): bar within the box, ii) first quartile (25th percentile): bottom part of the box, iii) third quartile (75th percentile): top part of the box. Whiskers represent observations outside the middle 50% and points represent outliers.

3.4 Geographically weighted regression

There is ~~a~~ considerable spatio-temporal variability in the strength of the correlation between the BA and environmental variables throughout the study area. Coefficient of determination R^2 values range spatially from 0.00 to 0.68 (S~~s~~lope inclination) depending on the variable and time interval (T~~t~~able 4). Explanatory power for all values tends to be weak, and ~~Along with the~~ topographic factors~~,~~ and Sclerophyllous vegetation shows ~~overall~~ the strongest ~~fit in the relationship~~ correlations with BA. The ~~rest of the~~remaining ~~v~~Vegetation types display a weak fit that ~~remains~~ is similar in both periods.

Table 4: Descriptive statistics of local R^2 per environmental factor for ~~period 1 (~~1970-1994 (P1) and for ~~period 2 (~~1995-2019 (P2).

	Slope aspect		Slope inclination		Sclerophyllous vegetation		Natural grasslands		Coniferous forest		Broad-leaved forest		Mixed forest	
Period	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2

Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Maximum	0.24	0.36	0.68	0.25	0.48	0.47	0.19	0.21	0.20	0.21	0.11	0.23	0.26	0.25
Mean	0.08	0.11	0.13	0.06	0.19	0.17	0.07	0.08	0.08	0.09	0.04	0.06	0.07	0.05
Median	0.07	0.1	0.1	0.05	0.16	0.15	0.08	0.06	0.05	0.03	0.03	0.05	0.04	0.05
Standard Deviation	0.08	0.12	0.08	0.04	0.12	0.11	0.03	0.05	0.03	0.03	0.02	0.05	0.05	0.04

Figure 14a and 14b depicts local R^2 results of the application of GWR between percentage of BA and topographic factors. Overall, highest values are concentrated mainly in western and central parts (closer to the coastline) of the study area ~~both~~ for both S~~s~~lope aspect and inclination. The proportion of variance explained by aspect is slightly greater in the second period with several cells being in the highest class (0.25-0.35). Despite having a strong local fit in the first period, both distribution and variability changed drastically for ~~s~~Slope inclination in the second period.

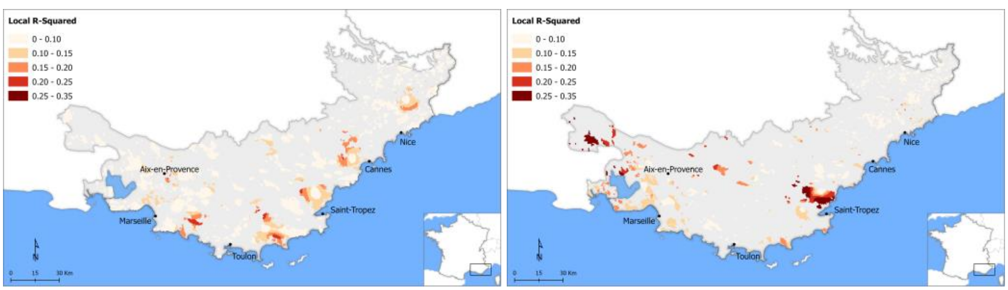

Figure 13~~14~~a: Spatial distribution of local R^2 between burned area and Slope aspect, for 1970-1994 (left) and 1995-2019 (right).

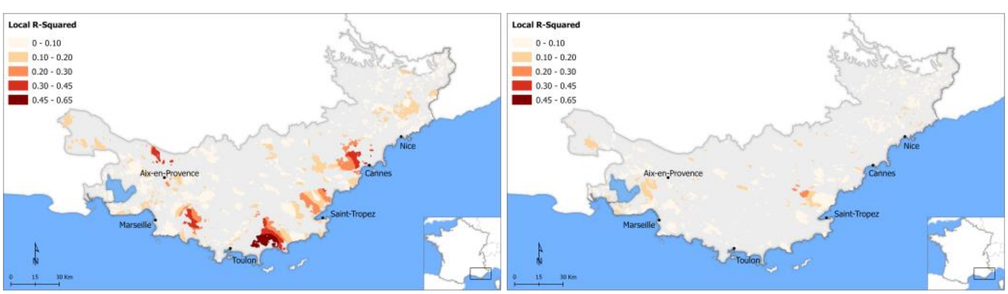

Figure 14b: Spatial distribution of local R^2 between burned area and Slope inclination for 1970-1994 (left) and 1995-2019 (right).

Figures~~-~~15a to 15e display local R^2 results of the application of GWR between percentage of BA and percentage of each vegetation type. Similar to topographic variables, Sclerophyllous vegetation exhibits the same spatial pattern of high R^2 values. A clear increase in local R^2 can be observed when moving towards the western part of the region, that is more evident in the first period. Low fits are found for both periods in the higher altitude areas, located mainly in north-eastern segments of the area. R^2 values for Natural grasslands are generally low and display small differences both in terms of space and variance. Explanatory variables related to forest categories show very weak fit in the relationship with BA. In addition, the general clustering patterns are quite different between the two periods.

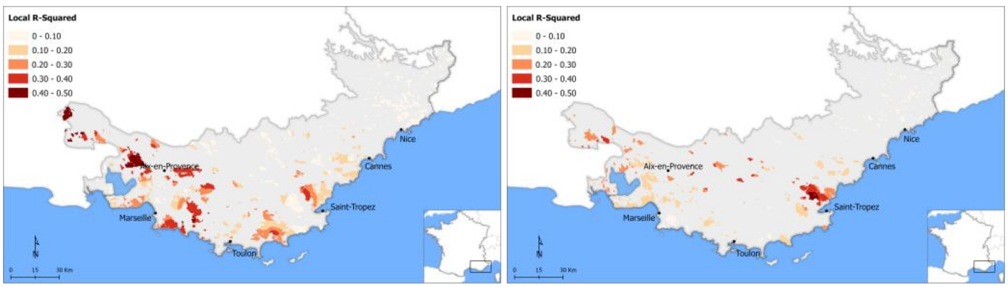

Figure 15a: Spatial distribution of local R^2 between burned area and % cover of Sclerophyllous vegetation for 1970-1994 (left) and 1995-2019 (right).

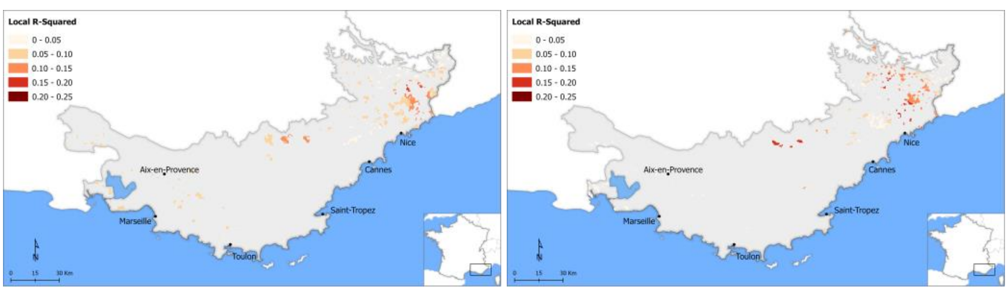

Figure 16: -Spatial distribution of local R^2 between burned area and % cover of Natural grasslands for 1970-1994 (left) and 1995-2019 (right).

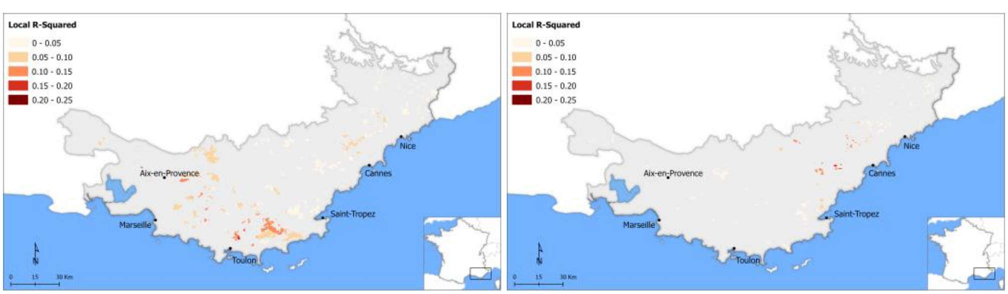

Figure 15c: Spatial distribution of local R2 between burned area and % cover of Coniferous forest for 1970-1994 (left) and 1995-2019 (right).

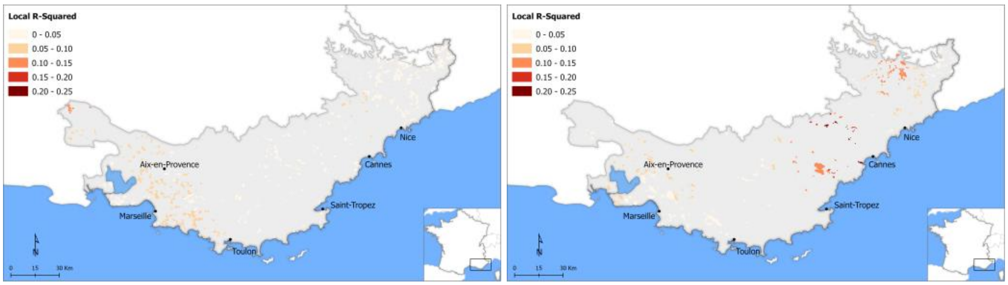

Figure 15d Spatial distribution of local R^2 between burned area and % cover of Broad leaved forest for 1970-1994 (left) and 1995-2019 (right).

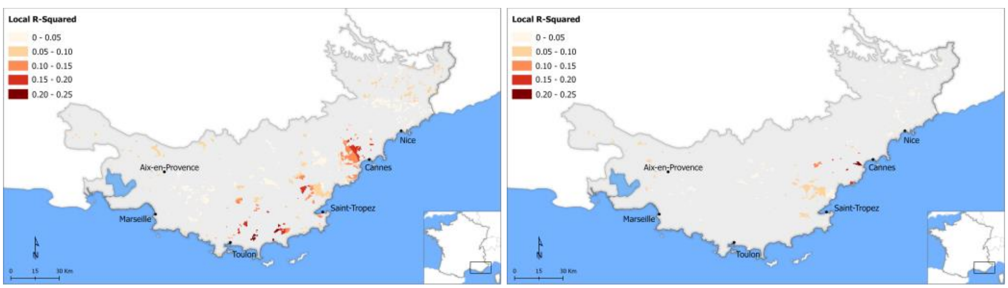

Figure 15e Spatial distribution of local R^2 between burned area and % cover of Mixed forest for 1970-1994 (left) and 1995-2019 (right).

4 Discussion

4.1 Fire history

BA in south-eastern France has undergone substantial changes over the last 50 years. Annually, BA varies considerably but clear declining trends are observed in the second part of the temporal interval under study. –Around half of the total BA (126,700 ha) was recorded in 5 years: 1979, 1986, 1989, 1990 and 2003. ~~characterize every~~ the ~~decade after 1990 and especially in the 2010-2019 interval, where BA represent only 5.3 % (13,649 ha) of the total, which is a 68.9 % decrease compared to the previous decade (2000-2009). Furthermore, around half of the total BA (126,700 ha) was recorded in 5 years: 1979, 1986, 1989, 1990 and 2003.~~ Due to ~~-~~particularly ~~the~~ catastrophic fires ~~between 1986 and 1990~~ in the 1980s, a new fire suppression policy ("Vulcain") was initiated that came fully into effect in 1994 (Direction de la Sécurité Civile, 1994). This new strategy focused on aggressively suppressing fire ignitions under any weather conditions in order to avoid ~~the~~ fire propagation ~~of fire~~ to the extent where suppression would become both more difficult and more expensive. Although Fire Weather Index values were not calculated here for the 3 administrative departments, Fox et al. (2015) noted a general increase in summer temperatures between about 1980 and 2010, so the fire-fighting policy had a major impact on the decrease in total BA after 1994. Only 2003 stands out as a big fire year in the 1995-2019 interval, and although it ~~, with the exception of 2003. This year~~ was the hottest/driest year on record in the Alpes-Maritimes, it remained within the range of BA values of the big 1980s fires ~~since at least 1973~~ (Fox et al., 2015).~~, and although its BA was greater than any other year since 1991, it was not exceptional compared to the 1979–1990 time interval.~~ Nonetheless, it raises~~d~~ doubts ~~regarding~~ about the sustainability of ~~the~~ rapid ~~extinction~~ suppression in extreme conditions ~~strategy and its ability to reduce fire risk in the long term since~~ resources are spread thinly over a greater number of ignitions (Curt and Frejaville, 2018).

4.1.1 Spatio-temporal analysis

The effect of the new firefighting strategy can also be viewed spatially:~~;~~ in general, fire patches are less large and are distributed over smaller geographic proximities with one another, and fire recurrence is lower ~~and clustered mostly near populated zones~~. ~~Despite the size of the study area and the physical proximity of the burn scars, different factors contribute to determine fire patterns before and after the policy change.~~ Spatio-temporal trends, however, vary from west to east according to the specific population and environmental contexts of each department. In the western part of the study zone, around Aix-en-Provence and Marseille, ~~where low vegetation continuity affects fire propagation and size,~~ hotspots, in the form of positive ~~-~~Z-scores~~index values~~, remain, and the ~~change~~ new~~in~~ fire-fighting strategy had less effect since fires were already limited in size by vegetation ~~patch sizes~~continuity. ~~Even though~~Although limited in area, multiple clusters of ~~significant increasing~~ positive trends are ~~spread~~ found in closer proximity to the built-up areas near Marseille and Aix-en-Provence in comparison to overall decreasing trends. ~~areas of i~~Increased human activity, ~~which is~~is known to affect fire ignition (Badia et al., 2011; Chas-Amil et al., 2013; Jiménez-Ruano et al., 2017; Lampin-Maillet et al., 2011)~~.~~ and in our context that can be potentially linked to the high arson activity found in the area (Curt et al., 2016). ~~Generally, wind speed is a particularly important factor for BA (Duane et al., 2015; Fernandes et al., 2016) and in this part especially since it is the main driver of large fires (Ruffault and Mouillot, 2015, 2017).~~ On the contrary, the central part of the study area, where most of the big fire occurs~~scars are located~~, the new fire policy ~~was able to~~ effectively limited ~~the~~ fire propagation ~~of fire~~ over the continuous ~~forest~~ vegetated cover that defines the region. This ~~region~~ zone displays the largest clusters of ~~decreasing~~ negative Z-scores, ~~and~~ decreasing BA with very few ~~and very limited areas with increasing BA~~positive values and low fire recurrence ~~which indicates that if trends remain similar over the next years, the area should possibly anticipate a further decrease in fire activity~~. Ganteaume and Barbero, (2019) provided evidence that large fires (>100 ha) ~~are~~ declined~~ing~~ sharply in the central segment of the study area after the introduction of the fire management policy and our results, using different methods, are coherent with their findings. ~~-~~Finally, i~~I~~n the eastern segment of the study area, ~~which involves different environmental characteristics (higher elevation, milder winds, high fuel continuity),~~ ~~many~~ frequent small ~~and~~ dispersed fire patches are found.~~,~~ Fire shapes are not elongated by wind direction compared~~ing~~ to ~~rest of the study area~~polygons in the western and central departments, and although negative fire occurrence trends dominate, particularly in the WUI band, there is a greater number of small positive patches compared to other zones.~~were reduced in the low-altitude WUI near-coastal areas~~

~~in the second period (1995-2019)~~. ~~Despite the higher fuel continuity and smaller effect of wind speed a similar pattern with the eastern section is present here; small but significant increasing trends appear closer to areas of increased human activity, which is known to affect fire ignition (Badia et al., 2011; Chas-Amil et al., 2013; Jiménez-Ruano et al., 2017; Lampin-Maillet et al., 2011).~~

4.2 Burned area and T~~t~~opography

~~4.2.1 Slope orientation~~aspect

S-facing slopes have the greatest BA, burn more frequently (Mouillot et al., 2003) and are more exposed to forest fires than other slopes due to both environmental factors (greater insolation and evapotranspiration) and WUI characteristics since S-facing slopes in southern France have more houses and therefore more potential ignition sources (Fox et al., 2018). ~~Generally~~ S-facing (sum of SW, S, SE) slopes play an increasingly important role over time, ~~which~~ and this could be linked to a combination of hotter summers and an increasing number of human dwellings on these slopes as growth rates on S-facing slopes in the Alpes-Maritimes were 4-5 times greater than on N-facing slopes in 1990-2012. ~~(Fox et al., 2018). However, considering that the fire policy is contributing in weakening the of fire-weather relationship (Ruffault and Mouillot, 2015), human presence has potentially a larger influence in that increase.~~

~~4.2.2 Slope inclination~~

Slope inclination favors fire propagation directly through more efficient radiative heat transfer (Rothermel, 1983) and increases the rate of spread and fire intensity (Csontos and Cseresnyés, 2015; Capra et al., 2018). In addition, slope inclination influences fire ignition and suppression indirectly through accessibility, solar radiation variations, fuel moisture, and fuel density which in turn influence flammability (Holden et al., 2009). In this study,~~.~~ ~~Normally, lowest inclinations~~Flat areas are most avoided by fire for several independent reasons: ~~since not only is~~ radiative heat transfer is less efficient on these slopes, ~~but~~ and flat areas are more densely inhabited and more easily accessible with denser road networks, so ~~the~~ lower fire preference probably depends as much or more on early suppression as on physical processes. The fire-avoidance of low slope inclinations strengthens over time, and this is coherent with more rapid suppression in this interval. BA in intermediate slope inclinations is not affected significantly by the change in firefighting strategy potentially due to factors that counter rapid suppression like more efficient radiative heat transfer, more difficult accessibility and presence of isolated or diffuse housing.

~~However, in the second period, lowest inclinations do not display the same fire avoidance. In addition, the results show a shift in BA from steeper to less steep slopes over time, and this suggests that the rapid suppression strategy put into place in the early 1990s reduced the propagation of fire from lower slopes where ignitions are expected to be greater to steeper wildland areas. Fires were contained more quickly and escaped to steeper wildland areas less frequently~~. ~~An opposite similar temporal shift from steeper to flatter slopes is observed for fire frequency in west-central Spain (Viedma et al., 2018). Considering the~~

~~negative relationship between slope inclination and human-caused fire ignitions found in Narayanaraj and Wimberly (2012), this can potentially be linked to the increasing human presence in flatter areas but also to more effective and rapid suppression. Due to the complex interactions between physical processes, human activities and topography, topographic roughness is frequently recognized as a significant but secondary predictor of fire occurrence after WUI characteristics in Euro-Mediterranean zone (Ganteaume and Jappiot, 2013; Nunes, 2012).~~

4.3 Burned area and Vegetation type

The role of vegetation in fire frequency and BA patches located in the Bouches-du-Rhône and Var departments was studied by Curt et al., (2013). Their case study reflects patterns observed here at a larger scale, namely that vegetation flammability is secondary to landscape organization. Large open patches of continuous fuel, as are found in the Var department, favor larger fires with longer return intervals than the small patchy wildland distribution in the Bouches-du-Rhône (Ganteaume and Barbero, 2019). Burned vegetation patterns observed here highlight the frequently cited role of Sclerophyllous vegetation (shrubland) (Ganteaume and Jappiot, 2013; Moreira et al., 2011; Oliveira et al., 2014a; Tessler et al., 2016). Shrublands both favor fire propagation in dry conditions (Baeza et al., 2002) and result from recurrent fires (Tessler et al., 2016). As Mermoz et al., (2005) suggested, the fire proneness of Sclerophyllous vegetation is connected to its ability to regenerate faster and ~~allow for~~ generate quicker fuel accumulation;~~,~~ ~~which~~ this also applies in our case since sclerophyllous vegetation covers the greatest area, greatest BA, greatest explained variance in the GWR analysis, and is one of two vegetation categories (with Natural grasslands) that have positive resource index values. ~~is the type burning the most while also growing within the region.~~ These results are coherent with the findings of others working ~~Additionally,~~ in Mediterranean environments~~,~~ where large fires tend to occur in landscapes with dense shrublands (Moreira et al., 2011; Ruffault and Mouillot, 2017) ~~and that is also the case here, since in all 5 years with the highest BA, sclerophyllous vegetation was the one with the greatest burned proportion~~. In a context where initial suppression is crucial to fire extinction, Sclerophyllous vegetation ~~bushlands~~ may resist early suppression better than other covers where initial propagation is perhaps slower. Moreover, firefighting assets appear to prioritize other types of vegetation during fire suppression since fire selectivity remains unchanged for bushlands, possibly due to the low cost of restoration (Oehler et al., 2012).

As other studies have concluded (Oliveira et al., 2014a), ~~n~~Natural grasslands display a high fire susceptibility. ~~Prior to the~~Despite the change ~~the~~ in the firefighting policy, grasslands are over-represented in BA in both time intervals and this may be due to faster initial propagation or accessibility issues, as for example in certain mid to high-altitude areas over the eastern section of the study area, where burned clusters of this vegetation type are found. Sheep grazing is a common practice in high alpine pastures of the Alpes-Maritimes department, and Natural grassland fires may be due to bush clearing operations by shepherds which resulted in uncontrolled wildfires that affected much larger areas than originally intended. ~~However, fire does not favor equally the specific type in the second period potentially due to improved fire suppression methods.~~

All three forest types (Broad leaved, Coniferous and Mixed) display a similar pattern characterized by fire avoidance, that is even more evident after the fire management policy change. This does not necessarily reflect a higher priority for suppression by firefighting assets over other vegetation types but may indicated that fires in these vegetation types take more initial time to spread than in bushland, so they are suppressed before becoming large fires.

5 Conclusion

In this study, results provide a coherent picture of the impact of a shift in firefighting strategy on fire occurrence and environmental characteristics. Burned area decreased sharply in SE of France after 1994 with the introduction of the new fire-fighting strategy. Rapid fire extinction was particularly effective in limiting big fires in the region. Large fire hotspots found mainly in the central parts disappear after the policy change, while new clusters of high fire recurrence appear in closer proximity to areas with increased human activity.

S-facing aspects have an increasingly bigger impact over time, and this may be linked to both environmental conditions and increased human presence on those slopes. Fire avoids low slope inclinations and even more so after the shift in fire suppression as flat areas are easier to access and more densely inhabited so lower fire preference is probably determined as much or more by early suppression as by physical processes (reduced radiative heat transfer).

Over half of the total BA in the last 50 years concerned sclerophyllous vegetation, thus confirming its strong association with high fire susceptibility and recurrence. Considering that sclerophyllous vegetation regenerates and expands faster than other vegetation types in the region, this may lead to an increase in fire risk in the future. Natural grasslands, even though they cover limited area and decline with time, are also preferred by fire which may be due to pastoral fires. On the contrary Broad leaved, Coniferous and Mixed forest are avoided by fire especially after the change in fire management policy.

Further ongoing exploitation of the fire GIS database in conjunction with WUI characteristics will likely further improve our understanding on the driving forces of BA and the impacts of fire-fighting strategies in the region.

Author contribution

CB established the fire geodatabase, carried out data processing, analyses, visualization and wrote the initial draft. DF performed the land cover modeling, contributed to the interpretation of the results and reviewed the manuscript. EB provided expertise for data analyses and reviewed the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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