Linking fire ignitions hotspots and fuel phenology: The importance of being seasonal

Sofia Bajocco\textsuperscript{a,}\textsuperscript{*}, Nikos Koutsias\textsuperscript{b}, Carlo Ricotta\textsuperscript{c}

\textsuperscript{a} CREAS - Council for Agricultural Research and Economics, Research Centre for Agriculture and Environment, Rome, IT-00184, Italy
\textsuperscript{b} Department of Environmental and Natural Resources Management, University of Patras, Agrinio, GR-30100, Greece
\textsuperscript{c} Department of Environmental Biology, University of Rome La Sapienza, Rome, IT-00185, Italy

\begin{abstract}
Fire ignitions tend to be aggregated in time and space creating a clustered spatio-temporal pattern that is mainly driven by climatic factors and the availability of ignition sources. The aim of this work is to identify the spatio-temporal distribution of wildfires hotspots in Sardinia (Italy) during 2009–2013 and to relate their dynamics with remotely-sensed NDVI-based fuel phenology patterns. We considered eleven bi-weekly time frames (TFs) and used kernel density (KD) estimation to spatialize the corresponding fire ignitions. Then, to identify zones of fire occurrence concentration, we performed a quartile classification of the KD values for each TF considered. Finally, we analyzed the spatio-temporal association between the ignitions hotspots and the remotely-sensed fuel phenology patterns by means of a correspondence analysis and a selectivity ratio. We found that wildfires hotspots are strictly related to anthropogenic pressure and to the spatio-temporal variation of fuel conditions in terms of both load and moisture: areas with less fires concentration proved to be mainly associated to coarse fuels with low seasonal NDVI variability; to the contrary, the fire hotspots resulted strictly correlated to fine fuels with high seasonal NDVI variability. Understanding the association between the seasonal distribution of wildfires hotspots and fuel phenology may allow the projection of fire ignition patterns to future, especially under changing climatic scenarios.
\end{abstract}

1. Introduction

Wildfires exhibit a marked seasonal cycle which is mainly driven by climatic factors and the availability of ignition sources. Interactions between climate, fuel and fire are complex, although it is widely demonstrated that climate is one of the key natural factors influencing both vegetation distribution and burning regime characteristics (Pourtaghi et al., 2016). While single fires may be caused by a number of different reasons (for instance for agricultural purposes like pasture renewal and crop stubble clearing), general fire regimes are primarily climate-driven (Bekker and Taylor, 2010). In the long term, climate affects fire regime in terms of fuel type and distribution (Marion et al., 2012). In the short term, variations in precipitation, temperatures, and drought periods have a direct effect on vegetation growth (i.e. fuel load) and flammable conditions (i.e. fuel moisture) (Archibald et al., 2013; Sarris and Koutsias, 2014).

In Mediterranean areas, live fuels represent the main component of the available fuel to fire (Pellizzaro et al., 2007). Flammability of living vegetation is influenced by several factors including the chemical properties of plants, moisture content and vegetation composition and structure (Van Altena et al., 2012). At the landscape scale, fuel availability and flammability are closely related to the phenological status of living vegetation, which directly affects wildfire pattern in time and space. Accordingly, fire occurrence is generally characterized by a strong annual cycle associated to the temporal patterns of environmental conditions and vegetation phenology (Ganteaume et al., 2013).

A number of studies have used remotely-sensed indices, such as the Normalized Difference Vegetation Index (NDVI), for monitoring the seasonal dynamics of vegetation from regional to global scales (Jeong et al., 2011; Fensholt et al., 2012; Ivits et al., 2012). NDVI is generally considered as a good proxy for vegetation primary productivity and biomass (Li et al., 2013; Piao et al., 2014). Accordingly, NDVI time series have been extensively used for monitoring coarse-scale vegetation dynamics (Ahl et al., 2006) and for providing information on key aspects of vegetation functionality, such as seasonality, productivity and inter-annual variability (Bajocco et al., 2015).

Fire seasonality, which is the sole component of fire regime in which climate has a greater impact than human activities, plays a crucial role in the impact of wildfire on ecosystem structure and function (Zhang et al., 2014; Huesca et al., 2009). However, anthropogenic land use

\* Corresponding author.
E-mail address: sofia.bajocco@creas.gov.it (S. Bajocco).

http://dx.doi.org/10.1016/j.ecolind.2017.07.027
Received 24 February 2017, Received in revised form 17 May 2017; Accepted 11 July 2017
1470-160X/ © 2017 Elsevier Ltd. All rights reserved.
management practices may also influence the temporal dynamics of wildfires (see Archibald, 2016). In agriculture, fire is used world-wide for soil fertilization (pre-seeding fires), or for burning crop residues (post-harvest fires; Yevich and Logan, 2003; Korontzi et al., 2006). In anthropogenic fire regimes, like in the Mediterranean region, fire ignitions also tend to be spatially aggregated due to the spatial autocorrelation of human activities (Caldarelli et al., 2001; Gonzalez-Olabarria et al., 2012). In these regions, identifying areas with very high probability of fire occurrence or “fire hotspots” may provide effective information for optimizing fire-fighting strategies and resources allocation (Carmel et al., 2009).

Forest fires hotspots are usually identified as real-time or daily satellite-based active fires detection (Caiszar et al., 2006; Hanton et al., 2013; Armenteras et al., 2016). Such approach is mainly focused on the single events detection, overlooking the general perspective of the phenomenon. To the contrary, some recent studies investigated the regional distribution patterns of wildfires hotspots relating them with driving factors (Kalabokidis et al., 2007), causes of ignitions (Gonzalez-Olabarria et al., 2012) and future fire regime scenarios (Salis et al., 2014).

In spatial analysis buffer impact areas are called “hotspots” and are determined by means of density clustering methods. One of the most commonly used method for visualizing multi-scale spatial variations in the frequency of point-based observations, such as fire ignition points, is kernel density (KD) estimation (Gonzalez-Olabarria et al., 2012; Koutsias et al., 2016). The flexibility of kernel methods has been previously demonstrated by many studies dealing with wildlife habitat and movement (Worton 1989). Kernel methods have been also used for spatializing point-based fire data, converting them into continuous surface representations and deriving maps of fire ignition density. The main advantage of using a continuous fire density layer is the possibility to integrate it with other types of spatially explicit data in order to estimate their driving factors, their geographic trends and their influence on the neighborhood (Podur et al., 2003; Koutsias et al., 2004; Amatulli et al., 2007).

The aim of this study was to investigate the spatio-temporal patterns of forest fire events occurred in Sardinia (Italy), a fire-prone area experiencing thousands of human-driven wildfires every year. The working hypothesis is that the spatial distribution of wildfires in Sardinia is not stable throughout the year, but rather changes as a function of the spatial patterns of fuel phenology. The first objective was hence to identify wildfires occurrence hotspots based on burning events recorded during 2000–2013 using kernel density interpolation techniques. The second objective was to explore the relationship between the seasonal dynamics of the identified wildfires hotspots and their remotely-sensed fuel phenology.

2. Study area

The island of Sardinia (Italy) is located in the western part of the Mediterranean Basin, between 38° 51’ N and 41° 15’ N latitude and 8° 8’ E and 9° 50’ E longitude and covers 24090 km² (Fig. 1). Sardinia has a complex topography; the average elevation is 338 m a.s.l. and the highest point is Punta la Marmora with 1834 m a.s.l. in the center of the island (Salis et al., 2015). The climate is characterized by mild rainy winters, dry hot summers and a remarkable water deficit from May to September. Most of the annual rainfall occurs in fall and winter; annual precipitation ranges from 500 mm along the southern coasts to 1200 mm in the mountains on the eastern side of the island. The mean annual temperature follows the same geographical pattern and ranges from 13°C to 18°C. During the summer season the daily maximum temperatures exceed 30°C. The average wind speed is moderate–high in both winter and summer seasons; west and north-west are the most frequent wind directions.

Sardinia has 1.7 million inhabitants, mostly concentrated in the cities of Cagliari and Sassari. The vegetation is influenced by both physical factors and a long history of anthropogenic pressure (fires, grazing, urbanization, agriculture, etc.). Forests cover about 16% of the island, and are mainly composed of Quercus ilex, Q. suber, Q. pubescens and Q. congesta. At higher elevations Q. pubescens forests are the most widespread oak formation. Pine plantations cover only 3%, mainly in the coastal areas, and include Pinus pinea and P. halepensis. Large areas (28%) are covered by shrublands (Mediterranean maquis and garrigue), comprised primarily of Potentilla lactuca, Arbutus unedo, Erica arborea, Myrtus communis, Olea europea, Phyllirea spp., Juniperus spp., Cistus spp. and Ephedra spp. Urban areas cover 3% of the island, while 50% of Sardinia is composed of anthropogenic land uses, such as agricultural lands, grasslands, pastures, vineyards and orchards (Salis et al., 2015).

3. Data

3.1. Fuel phenology data

To relate fire occurrence with fuel seasonality, we used the phenological map of Sardinia produced by Bajocco et al. (2015). To realize the map, remotely sensed NDVI images from 2000 to 2013 were used. NDVI is calculated as the normalized ratio of red and near-infrared (NIR) surface reflectances: (NIR – RED)/(NIR + RED); it ranges between −1 and 1. The images were extracted from the 16-days MODIS maximum value composite product MOD13Q1 of the MODIS satellite at 250 m pixel resolution (https://lpdaac.usgs.gov/products/modis_products_table/mod13q1). Late fall and winter scenes revealed several low quality and noisy pixels regions due to bad weather events. Therefore, we focused only on late spring-early autumn scenes, i.e. eleven yearly MODIS NDVI images from Julian day 113 (April 23rd) to Julian day 273 (October 1st). The 16-days time frames (TFs) used for generating the map were: 23 April–8 May (TF1); 9–24 May (TF2); 25 May–9 June (TF3); 10–25 June (TF4); 26 June–11 July (TF5); 12–27 July (TF6); 28 July–12 August (TF7); 13–28 August (TF8); 29 August–13 September (TF9); 14–29 September (TF10); 30 September–15 October (TF11).

The phenological map is composed of 60 phenologically

Fig. 1. Location of the study area.
homogeneous landscape units. They were obtained by segmenting the images derived from the Temporal Fourier analysis of the mean NDVI temporal profiles of each pixel. The 60 units were then hierarchically clustered into four phenological fuel classes (from PFC1 to PFC4; Fig. 2) according to an increasing gradient of seasonal NDVI amount and a decreasing gradient of seasonal NDVI variability. According to Bajocco et al. (2015), the PFCs proved also to be associated to specific land uses (based on the CORINE Land Cover map; EEA, 2007) and climatic regions (based on GIS NATURA, 2005) (see Table 1).

3.2. Fire occurrence data

We determined the historical pattern of ignitions in Sardinia from 2000 to 2013 using a wildfire occurrence database recorded by the regional Forest Service. For each fire record, the database provides information on the date of ignition, the coordinates of the ignition point, and fire size. During the period 2000–2013, Sardinia experienced 38,217 wildfires, with 209,114 ha of total burned area. Wildfires are typically concentrated from June to September with a peak of ignitions in July, while relatively low activity was observed from late fall to early


<table>
<thead>
<tr>
<th>Fuel type</th>
<th>Seasonal NDVI</th>
<th>Main Land Cover types</th>
<th>Main Climatic types</th>
<th>Mean altitude (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PFC1 Fine fuel</td>
<td>Very high</td>
<td>Arable lands,</td>
<td>Mediterranean</td>
<td>142</td>
</tr>
<tr>
<td>PFC2 Fine fuel</td>
<td>High</td>
<td>Urban areas, Permanent crops, Heterogeneous agricultural areas and Natural grasslands and pastures</td>
<td>Mediterranean, Transitional-Temperate</td>
<td>278</td>
</tr>
<tr>
<td>PFC3 Coarse fuel</td>
<td>Low</td>
<td>Permanent crops, Heterogeneous agricultural areas, Natural grasslands and pastures</td>
<td>Transitional-Mediterranean, Transitional-Temperate</td>
<td>391</td>
</tr>
<tr>
<td>PFC4 Coarse fuel</td>
<td>Very low</td>
<td>Forest and Shrublands</td>
<td>Transitional-Mediterranean, Transitional-Temperate</td>
<td>507</td>
</tr>
</tbody>
</table>

| Fig. 3. Seasonal distribution of fire ignitions in Sardinia for the period 2000–2013. |

4. Methods

4.1. Kernel density estimation of the ignition points

The ignition points in each TF were converted to a continuous density map of fire events by means of kernel density estimation similar to Koutsias et al. (2015). For the kernel density interpolation, we used the fixed kernel approach, which defines a constant smoothing parameter that remains the same over the entire study area and ensures the same weighting of the point observations over the areas with different degrees of density (Worton, 1989). The kernel density estimator is mathematically defined as (Silverman, 1986; Worton, 1989; Seaman and Powell, 1996):

\[
\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K \left( \frac{x - X_i}{h} \right)
\]

where \( n \) is the number of points, \( h \) is the smoothing parameter or the bandwidth, \( K \) is a kernel density function, \( x \) is a vector of coordinates that define the location where the function is estimated, and \( X_i \) are vectors of coordinates that define each observation \( i \). Among the many possible kernel functions (see Levine 2008) we selected a bivariate kernel density function, which is the most commonly used function for density estimation (Kelcill and Diggle, 1995).

The size of the smoothing parameter \( h \) is another critical parameter of the kernel density estimation, since it controls the degree of smoothing of the estimates. Small bandwidths allow nearby observations to dominate the density estimate, while large bandwidths favor distant locations (Worton, 1989; Seaman and Powell, 1996). According to Silverman (1986), the choice of the bandwidth depends mostly on the purpose for which the density estimate is used. In our study, we applied the kernel density interpolation to different subsets of ignition points which correspond to various 16-days intervals with a different number of point observations. Therefore, the size of the smoothing parameter was determined in relation to the nearest neighbor distances of the fire ignition points for avoiding over- or under-smoothing of the estimates. The size of the kernel was 4000 m, which is actually the standard deviation of the bivariate probability density function used in our study. Since the integral of the bivariate probability density function over the whole available spatial range is equal to unity, the estimated kernel density values of fire events are expressed as absolute densities, meaning that the total sum of the densities of each of the 16-days kernel surfaces represents the total amount of fires within these 16-days intervals.

4.2. Identification of the wildfires hotspots

In order to identify zones of fire occurrence concentration, we performed a quantile classification of the KD values for each TF considered. In the quantile classification method, intervals (i.e. quantiles) are selected so that the number of observations in each interval is the same and so each class contains the same number of features. If each interval contains 25% of the observations the result is known as a quartile classification. We grouped the kernel density estimates of fire events in each TF into four quartiles (Q1–Q4). For each TF, the spatial distribution of the upper quartile (Q1) of kernel density values was identified as the hotspot area of fire events in that time frame, i.e. the zone with the highest concentration of fire ignitions.
4.3. Linking fire hotspots and fuel phenology

For all TFS, we calculated the mean NDVI value of each quartile. Then, to relate the spatio-temporal dynamics of fire ignitions with the remotely sensed fuel phenology patterns in Fig. 2, we randomly located 1000 points, extracted the corresponding PFC and KD quartile for each TF, and then we performed a correspondence analysis (CA). Correspondence analysis is used to characterize the relationships between two nominal variables; in our study those of phenological fuel classes (PFC1 to PFC4) and the quartile classification of the kernel density values (Q1–Q4) for each TF considered. Correspondence analysis, which is a multivariate statistical technique similar to principal component analysis, implies categorical rather continuous data and is used to reduce the dimensionality of a data matrix and visualize it in a subspace of low-dimensionality (Nenadic and Greenacre, 2007). CA provides factor scores (coordinates) which they are used to show graphically the association between the corresponding row and column variables in a contingency table.

Finally, to relate the spatio-temporal dynamics only of the fire hotspots identified with the remotely sensed fuel phenology patterns, for the upper quartile (Q1) of each TF we calculated the degree of association as the proportion of pixels belonging to each PFC divided by the proportion of that PFC in the entire study area. This ‘selectivity ratio’ (α) takes values in the range [0, ∞]. Values larger than 1 denote PFCs that occur in Q1 more frequently than expected by chance, thus implying a positive association of that PFC with the wildfire hotspots; values lower than 1 denote PFCs that occur in the hotspots less frequently than expected (Bajocco and Ricotta, 2008).

5. Results

Fig. 4 shows the quartile classifications of the kernel density estimates of each TF. At the beginning of the fire season, the fire hotspots (Q1) show a rather scattered and fragmented distribution. From TF3 to TF6 (i.e. from late May to late July) the highest values of the kernel density estimates tend to coalesce forming a large connected patch in the southwestern part of Sardinia. At the end of the fire season, from TF9 to TF11 (i.e. from late August to mid October) a new, large and connected fire hotspot is formed in the northwestern portion of the island.

The temporal NDVI profiles of each quartile (Fig. 5) show that the fire hotspots are associated to the lowest NDVI values across the entire fire season, with a marked dry period lasting from late May to late August (TF3–TF9). To the contrary the NDVI profiles of the other quartiles are characterized by higher remotely sensed plant biomass and a less intense dry season.

At the same time, the correspondence analysis shows a strong correlation between the phenological fuel classes (PFC1 to PFC4) and the quartile classification of the kernel density values (Q1–Q4) all over the fire season (Fig. 6); for each TF considered, the first two CA factors explain over the 94% of the variability of the system and the distribution of the different quartiles in the PFCs ordination space reflects their fuel phenology characteristics. In detail, each fire density quartile (Q1–Q4) resulted associated with a different phenological class (PFC1–PFC4, respectively) and the clearest correspondence patterns...
occur from TF3 to TF7.

Finally, the temporal profiles of the degree of association of the four PFCs with the wildfire hotspots (Fig. 7) show that the pixels in Q1 are positively associated with the phenological fuel classes PFC1 and PFC2 and negatively associated with the phenological fuel classes PFC3 and PFC4. In particular, PFC1 shows higher selectivity values with σ ranging from 1.31 to 2.83, thus representing the most fire-prone class, and reaches its maximum value at TF4. By contrast, PFC2 shows a lower degree of association with the pixels in Q1 (1.01 ≤ σ ≤ 1.57) and a peak around TF10.

6. Discussion

Previous studies have shown the strong influence of pheno-climatic variables on wildfires occurrence on an annual or inter-annual scale (Bajocco et al., 2010; De Angeli et al., 2012; Fréjaville and Curt, 2017) and recognized climate as one main fire driver, by determining the variability in the resource to burn (fuel amount) and the occurrence, intensity and duration of drought conditions (fuel moisture) (Lehmann et al., 2014).

Results from the present study demonstrated that fuel phenological patterns also affect the seasonal behavior of anthropogenic fires directly shaping the spatio-temporal distribution of fire ignitions across the landscape: wildfires hotspots through the fire season mainly occur where and when vegetation is most moisture stressed within the annual cycle. Such findings confirmed that climate forcing still represents a key controlling factor of burning, even in contexts of human-driven fires (Bajocco et al., 2015; Venäläinen et al., 2014) where the anthropic component, affecting fire starting and fuel characteristics, may confound the relationships between fire behavior and bioclimatic conditions (Vázquez et al., 2002).

The seasonal dynamics of fire hotspots spatial distribution detected considerable geographic variation across the study area, with the majority of ignitions occurring in south-west Sardinia, which represents the area with the highest ignition risk during the entire fire season. This portion of Sardinia is characterized by a dry Mediterranean climate and flat morphology, mainly covered by agricultural lands. Here, fire occurrence is favored on one hand by the extensive presence of fine fuels, that dry more quickly and can thus burn more easily after short periods of dry weather, and on the other hand by the ignition energy provided.
by the intense anthropogenic pressure (Bajocco et al., 2015). At the end of the fire season, a second large hotspot is formed in the northwestern part of Sardinia; this evidence demonstrates the tendency of late wildfires to concentrate in the inner part of the study area where climate is wetter, elevations are higher and fuel is coarser and hence dries later in the season (Bajocco and Ricotta, 2008; Kane et al., 2015).

As recently demonstrated by Aragàrza et al. (2015) in Central Argentina, Kane et al. (2015) and Littel et al. (2016) in North America, and Urieta et al. (2015) in Mediterranean-type regions, fuel moisture content is a key factor for the ignition of fires, both limiting the biomass load and favoring the vegetation flammability.

According to these studies, the mean NDVI temporal profiles of the four KD quartiles showed that there is a close connection between fires number and the spatio-temporal dynamics of fuel conditions, highlighting the role of remotely sensed vegetation phenology as an important driver of fire ignition. Such findings are also confirmed by the CA results which demonstrate that the fire density quartiles follow a gradient of increasing fuel load (from grassland to woody vegetation) and decreasing fuel variability (from high to low summer desiccation).

In the same vein, the temporal profiles of the degree of association of the hotspots pixels with the four phenological fuel classes highlighted a marked association of the wildfire hotspots with the phenological class characterized by the firer fuels, i.e. PFC1 and PFC2. Both classes are generally characterized by drier climates, and a strong prevalence of anthropogenic land uses (see Table 1), confirming that even if human-driven, the viability of a fire to start is highly climate-dependent (Vázquez et al., 2002). Nonetheless, in line with the CA results, wildfire hotspots shows the strongest positive association with PFC1, with a peak in late spring–early summer. On the other hand, PFC2, which contains a higher proportion of natural land uses in more internal areas (Bajocco et al., 2015), shows a lower level of association with wildfire hotspots and, unlike for PFC1, due to the less favorable fuel conditions of the class, the maximum values of association are reached only towards the end of the fire season, after longer periods of dry weather. The interaction between climate and ecosystems governs the dynamic of fuel moisture (Nelson, 2001). Fire vegetation desiccates rapidly after the dry season starts, and are thus predisposed to early season fires, as is the case in grasslands and croplands. Wooded vegetation has a slower moisture dynamic, and fire sensitivity may be reached only late in the dry season, as in shrublands and forests (Le Page et al., 2010).

Early, middle and late season fires have different ecological impacts. Since the vegetation gets drier over the course of the dry season, middle and late season fires tend to spread fast and with high intensity, and may be difficult to control and suppress until reaching a landscape fire break (Le Page et al., 2010). On the contrary, early fires tend to be easily controlled since the vegetation is greener, and the fire senescence process is at its beginning (Cheney and Sullivan, 2009). Furthermore, as demonstrated by our results, while early fire hotspots are mainly concentrated only in PFC1, the latest fire ignitions involve different types of vegetation phenology, i.e. PFC1 and PFC2, requiring different types of prevention actions and intervention measures.

In conclusion, the proposed methodology provides a modeling tool to identify wildfires hotspot distribution through time and space and to relate them with the coarse-scale phenological dynamics of fuels.

The detection of geographic clusters of fire occurrence can assist in the identification of areas at greatest risk and the selection of locations for more intensive analyses focusing on the causes and effects of wildland fires (Vega Orozco et al., 2012). From a more operational viewpoint, the detection of zones with an intense and repeated history of burning and their spatio-temporal dynamics during the fire season may constitute a valuable tool for optimizing fire prevention strategies and for efficiently allocating fire fighting resources. In a perspective of climate change, knowing the association between the seasonal distribution of wildfires hotspots and fuel phenology may allow to predict future fire behavior under spatial and temporal shifts in the vegetation dynamics (Jeong et al., 2011; Zhu et al., 2012; Forkel et al., 2013; Garonna et al., 2014) and hence to adapt fire prevention and fighting strategies to the new environmental conditions.

Ultimately, the resulting classification maps of fire seasonality hotspots may provide a relevant information source for future studies related to the changes in the spatio-temporal patterns of fires at a regional scale.

This initial investigation of fire and vegetation phenology patterns may serve as a starting point, on one hand, to create a baseline understanding of current fire occurrence patterns in a perspective of climate change scenarios, and, on the other hand, to consider the role that the seasonality of fire has as a local land management tool when developing precautionary strategies.

Acknowledgement

We acknowledge the “Corpo Forestale e di Vigilanza Ambientale” of Sardinia for their assistance and willingness to share their field data and scientific advice.

References

GIS NATURA, 2005. Il GIS della conoscenza naturale del territorio. Ministero dell’Ambiente e della Tutela del Territorio e del Mare (DdT), Roma.