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The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain

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Abstract

In this paper we investigate spatial-temporal associations of fire weather danger and fire regime features from 1979 to 2013. We analyze monthly time series of fire activity (number of fires and burned area) and fire weather danger rating indices (Fire Weather Index, Burning Index and Forest Fire Danger Index) at two spatial scales: (i) regionally, splitting the Spanish mainland into Northwest, Hinterland and Mediterranean regions; and (ii) locally, using the EMCWF grid. All analyses are based on decomposing time series to retrieve differential indicators of seasonal cycles, temporal evolution and anomalies. At regional scale we apply lagged cross-correlation analysis (4 lags or months before fire) to explore seasonal associations; and trend detection tests on the temporal evolution component. At the local scale, we calculate Pearson correlation coefficients between each individual index and the 18 possible fire-activity subsets according to fire size (all sizes, >1 ha and >100 ha) and source of ignition (natural, unintended and arson); this analysis is applied to both cycles, temporal and anomalies series.

Results suggest that weather controls seasonal fire activity although it has limited influence on temporal evolution, i.e. trends. Stronger associations are detected in the number of fires in the Northwest and Hinterland regions compared to the Mediterranean, which has desynchronized from weather since 1994. Cross-correlation analysis revealed significant fire-weather associations in the Hinterland and Mediterranean, extending up to two months prior fire ignition. On the other hand, the association between temporal trends and weather is weaker, being negative along the Mediterranean and even significant in the case of burned area. The spatial disaggregation into grid cells reveals different spatial patterns across fire-activity subsets. Again, the connection at seasonal level is noticeable, especially in natural-caused fires. In turn, human-related wildfires are occasionally found independent from weather in some areas along the northern coast or the Ebro basin. In any case, this effect diminishes as the size of the fire increases. Our work suggests that for some regions of mainland Spain, these fire danger indices could provide useful information about upcoming fire activity up to two months ahead of time and this information could be used to better inform wildland fire prevention and suppression activities.

Keywords: wildfire, time series, seasonal cycles, trend, weather, fire regime

1. Introduction

Understanding the complexity and dynamics of fire regimes is growing in importance as the size and severity of wildfires increase in many regions (Falk et al., 2011). Many factors are involved when defining fire regimes; it is widely recognized the crucial role humans play in wildfire incidence (San-Miguel-Ayanz and Camiá, 2009) but it is also indisputable the remarkable influence exerted by weather and climate. Generally speaking, wildfires are the result of complex human–environment interactions and synergies (Koutsias et al., 2012; Krebs et al., 2010; Liu et al., 2012; Liu and Wimberly, 2016). The final affected area depends on the fire conducive weather, fuel availability and topography (Drobyshev et al., 2012; Parisien et al., 2011; Whitman et al., 2018), but also on fire suppression and site accessibility, thus shaping the resulting fire perimeter (Flannigan et al., 2009; Krebs et al., 2010; Papadopoulos et al., 2013; Shakesby and Doerr, 2006). Notwithstanding, weather factors influence both fire ignition and spread (Thompson et al., 2011). For instance, coincident high temperatures and extended drought circumstances may promote larger fires (Camia and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2014; Urbieta et al., 2015).

In Spain, several works report an overall decrease of wildfire frequency along the Mediterranean coastlands but an intensification in the remaining territory (Turco et al., 2016). Likewise, a recent paper by Jiménez-Ruano et al. (2017b) reported increased fire activity in the Northwest area of Spain, one of the most fire-affected regions in Europe (Koutsias et al., 2016; Pausas and Fernández-Muñoz, 2012). Furthermore, winter fires and large fires are more frequently observed, partially induced by human activities (Jiménez-Ruano et al., 2017a) but also related to the lengthening of the fire season (Jolly et al., 2015). Therefore, we can safely assume fire dynamics are, to some extent, linked to climate variability. As a matter of fact, some studies already suggest a transition towards more climate-driven fire regimes at a global scale (Pechony and Shindell, 2010) and an increased role of climate factors in fire occurrence (Rodrigues et al., 2016).

However, one of the main undefeated challenges of fire science is to ascertain the extent to which climate and human factors are influencing fire regime dynamics. In other words, what role does weather play in the evolution and temporal behavior of fire incidence? Does it depend on the source of ignition? A number of studies on wildfire incidence have focused on current climate (Abatzoglou and Williams, 2016; Bedia et al., 2013; Parente et al., 2016; Pausas, 2004; Turco et al., 2014) as well as future scenarios (Boulanger et al., 2014; Mori and Johnson, 2013; Perera and Cui, 2010); but studies examining the temporal weather-fire interactions still has room for improvement.

In this sense, a widespread approach to measure the influence of weather on wildfires has been the use of fire weather danger rating indices. The Canadian Fire Weather Index (FWI) is the most established index being applied worldwide (Van Wagner, 1987); without being exhaustive, we find examples of use of FWI in North America (Jain et al., 2017; Turetsky et al., 2004; Wang et al., 2015; Wotton et al., 2017), Europe (Dupire et al., 2017; Viegas et al., 2006), and also in Iberian Peninsula (Bedia et al., 2012). Likewise, other rating indices have been explored such as the United States Burning Index (BI) (Schoenberg et al., 2007) or the McActhur's Forest Fire Danger Index (FFDI) in Australia (Sanabria et al., 2013). However, few works compare (i.e., Nolasco and Viegas, 2006; Pérez-Sánchez et al., 2017) the performance of different fire weather indices.

In this study, we investigate the temporal association between weather factors and fire incidence, using fire weather rating indices as a proxy of short-term weather conditions. We analyze temporal correlations between monthly time series of fire weather danger indices (FWI, BI and FFDI) and fire regime features (fire frequency and burned area) in the period 1979 to 2013. Analyses were carried out at two different spatial levels; regions, splitting mainland Spain into three homogenous areas in terms of fire activity (i.e. term that refers to two variables: number of fires and total burnt area combination) and climate conditions; and at a local level, using the European Centre for Medium-Range Weather Forecasts (ECMWF) grid (0.75ºx0.75º, roughly 82x82 km). Time series of weather indices and fire data were decomposed (season, trend and remainder), analyzed and compared using a combination of correlation and trend detection procedures. Our main goals are (1) to determine the extent to which weather controls intra and inter-annual fluctuations of number of fires and burned area at a regional scale, and (2) to detect spatial patterns according to fire size and ignition source.

2. Materials and methods

2.1. Study area

The study area is mainland Spain (thus excluding both the Balearic and Canary archipelagos and the autonomous cities of Ceuta and Melilla). Spain is very biophysically diverse, presenting a wide variety of climatic, topographical, and environmental conditions. Mainland Spain is dominated by two biogeographical regions. The Eurosiberian region covers most of the northern area of the country. It is characterized by an Oceanic climate (according to Koeppen's climate classification - *Cfb*), mostly covered by various types of vegetation from deciduous oak (*Quercus robur, Fraxinus excelsior* or *Fagus sylvatica*) and ash to evergreen oak woodlands, but this region is also heavily dominated by forest plantations such as *Pinus radiata* and *Eucalyptus globulus*. The Mediterranean region covers the remaining territory. Hot-summer Mediterranean (*Csa*) and cold semi-arid (*BSk*) climates characterize this area, which therefore has notably drier and warmer conditions than the Eurosiberian region. These conditions, coupled to human activity, favour complex mosaics of agricultural systems and plant communities. Sclerophyllous and evergreen vegetation, such as *Quercus ilex* and thermophilous scrublands (maquis and garrigues formations), dominate the region, and forest areas mainly consist of pines (*Pinus halepensis*, *Pinus sylvestris*, *Pinus pinea or Pinus pinaster*). Furthermore, bioclimatic (altitudinal) belts exist within each region in mountain areas such as the Pyrenees along the French border or Sierra Nevada on the southern Mediterranean coast.

Due to the variety of conditions the Spanish Ministry of Agriculture and Environment outlined 3 major regions (Figure 1) portraying homogenous fire regimes: Northwest (NW), Hinterland (HL) and Mediterranean (MED). The NW region includes the autonomous communities of Galicia, Asturias, Cantabria and the Basque Country, as well as the provinces of León and Zamora. This region is located broadly within the Eurosiberian region, excluding the Pyrenees mountain ranges. The HL region includes all of the autonomous communities without coastline, except for the provinces of León and Zamora (which belong to NW). HL is located in the transition inland between the Mediterranean and Eurosiberian regions, thus sharing climate influence and plant species from both of them. Finally, the MED region, situated completely within the Mediterranean biogeographical region, includes all the autonomous communities along the Mediterranean coastlands, as well as the western provinces of Andalusia.

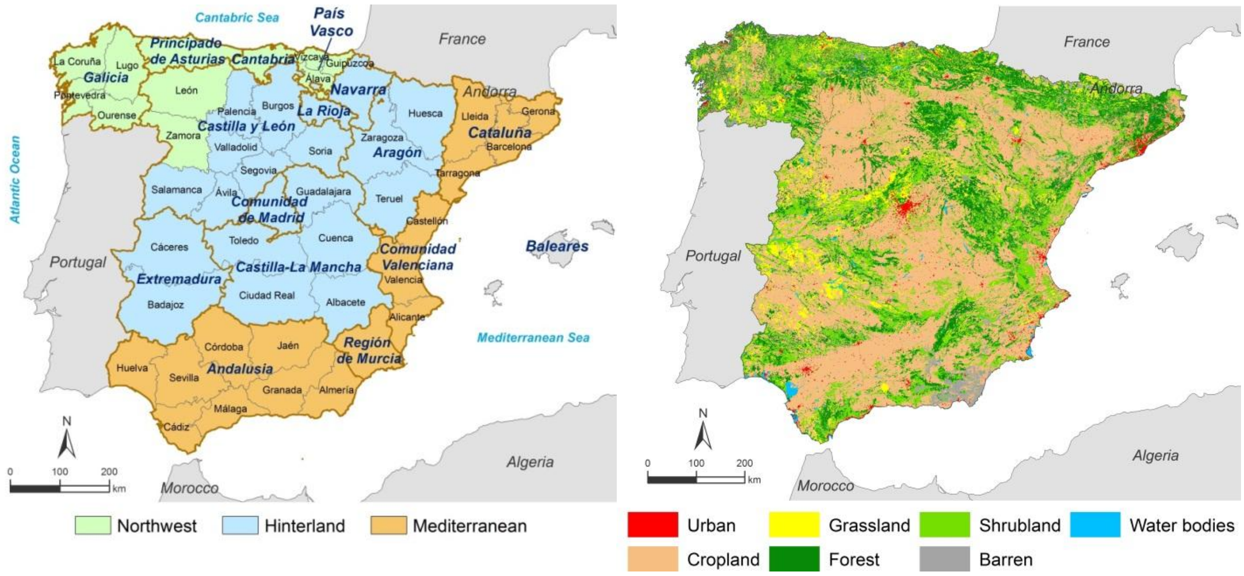

Figure 1. Spatial distribution of the three regions considered (Northwest, Hinterland and Mediterranean), also NUTS3 and NUTS2 units in mainland Spain (left) and generalized land cover from Corine Land Cover 2006 (right).

2.2. Fire weather danger rating indices

We have explored 3 of the most widespread fire weather danger rating indices in the literature: the Canadian Fire Weather Index (FWI), the US Burning Index (BI) and Australian Forest Fire Danger Index (FFDI). These indices summarize weather conditions related to the ‘burning potential’; nonetheless FWI and BI also reflect fuel moisture whereas FFDI is a pure meteorological index.

FWI was computed following the Van Wagner and Pickett (1985) specifications, using an specifically-written C++ library. We used noon weather (either 12.00 or 13.00 local standard time) daily gridded data from the ECMWF Interim Reanalysis (Dee et al., 2011). The US BI parameters (fuel moistures and indices) were computed following Bradshaw et al. (1983). The final BI index represents the expected rate of spread and heat release of a given fire. Again, gridded data from the ECMWF was employed to build the index. To ensure spatial-temporal homogeneity, FWI and BI calculations were constrained to fuel model G (short needle, heavy dead), because this heavily weights long time-lag fuels, thus better representing seasonal wetting-drying cycles (Jolly et al., 2015). Finally, FFDI was calculated following the steps established by McArthur and expressed as equations by Noble et al. (1980). The Drought factor for these equations was calculated using the improved formula presented by Griffiths driven by the Keetch-Byram Drought Index, which was calculated using daily maximum temperature and precipitation from each ECMWF reanalysis dataset and mean annual precipitation values from the WorldClim climate dataset (Hijmans et al., 2005). See Jolly et al. (2015) for deeper insights on the calculation of the indices. Figure 2 shows the overall workflow followed to calculate every index.

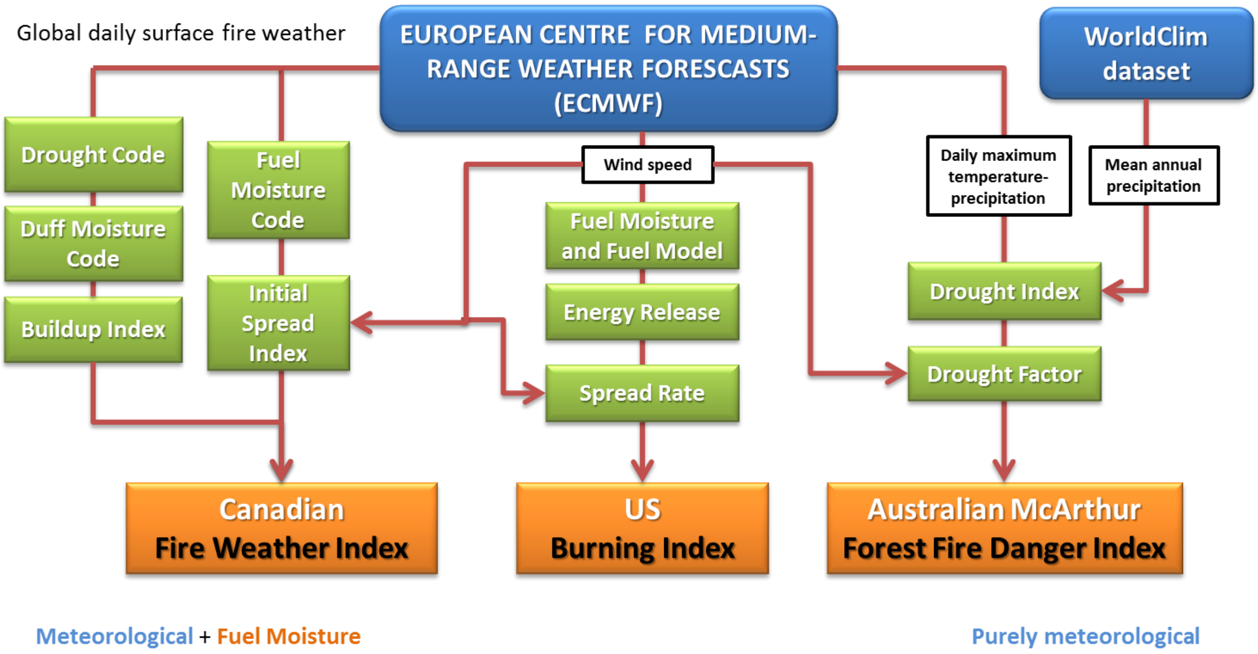

Figure 2. Overall workflow to obtain the Fire Danger Weather Rating Indices employed in the study (see Jolly et al., 2015, for more details).

2.3. *Fire data and fire-activity subsets*

Wildfire information in the period 1979-2013 was retrieved from fire reports in the Spanish General Statistics Forest Fires database (EGIF), compiled by the Spanish Department of Defense Against Forest Fires The EGIF database stands out for its precision and completeness, since is one of the oldest wildfire databases in Europe, beginning in 1968 (Vélez, 2001). Among other valuable information, fire reports provide the starting point of each fire event –recorded on a 10x10 km reference grid–, the ignition source, the affected burned area size, and detection date.

Table 1. Number of fires and burned area summary per ignition cause and fire size globally and regionally for the period 1979-2013.

	Fire frequency			Burned area (ha)		
	Spanish mainland (whole study area)					
Size	**Natural**	**Unintended**	**Arson**	**Natural**	**Unintended**	**Arson**
All	20,336	95,607	273,043	373,971	1,175,281	2,734,781
>1 ha	4,923	39,706	124,316	372,225	1,163,028	2,700,633
>100 ha	348	1,521	4,601	333,684	867,602	1,628,286
	Northwest					
Size	**Natural**	**Unintended**	**Arson**	**Natural**	**Unintended**	**Arson**
All	3,848	26,408	223,149	38,122	190,636	1,777,329
>1 ha	1,308	12,142	101,116	37,673	187,120	1,748,864
>100 ha	74	345	3,208	26,405	88,565	879,687
	Hinterland					
Size	**Natural**	**Unintended**	**Arson**	**Natural**	**Unintended**	**Arson**
All	10,785	38,104	29,554	177,672	429,890	453,538
>1 ha	2,474	15,791	14,226	176,800	425,030	450,019
>100 ha	193	621	762	157,617	311,510	327,553
	Mediterranean					
Size	**Natural**	**Unintended**	**Arson**	**Natural**	**Unintended**	**Arson**
All	5,703	31,095	20,340	158,177	554,755	503,913
>1 ha	1,141	11,773	8,974	157,751	550,878	501,750
>100 ha	81	555	631	149,662	467,527	421,047

Two sets of fire-related time series were constructed at a monthly level: the overall fire frequency (N -number of fires) and burned area (BA - total affected area in has) were summarized at a regional level (Table 1); additionally fires were assign to its corresponding ECMWF-grid (Figure 3). Fire data was then split into several fire-activity subsets of ignition source (natural, negligence/accident and arson) and fire size (All sizes, >1 ha and >100 ha). Negligence and accidental fires will be further referred to as 'unintended'.

1.1. Methods

Fire-weather relationships were analyzed in 3 stages: (1) first we decompose time series of weather data and fire features; (2) then we investigate spatial-temporal associations at a regional level; finally, (3) we try to identify spatial patterns in fire-weather associations at grid level. The whole process involves several statistical procedures. We use time series decomposition to split temporal observations into its main components, cross-correlation to investigate seasonal cycles, Mann-Kendall and Sen's slope for trend detection and Pearson's correlation coefficient to explore spatial patterns of association at local level.

All statistical procedures, maps and plots were obtained using the R statistical programming language (R Core Team and R Development Team Core, 2017), packages *astsa* for cross-correlation and *trend* and Mann-Kendall and Sen's slope tests; *raster* and *rgdal* for spatial data manipulation; *stats* for Pearson's correlation analysis; and *ggplot2* for mapping and plotting.

1.1.1. Decomposing monthly time series

Time series of fire activity and weather indices were decomposed using Seasonal-Trend Decomposition (STL; Cleveland et al. 1990). STL is a very versatile and robust method to divide time series allowing the detection of both gradual changes (trend) and cycles (season). More importantly, decomposing enables further analysis such as cross-correlation (CC) whose performance is affected by underlying temporal structures; hence it is strongly recommended that time series were de-trended beforehand.

STL consists in a sequence of Locally Weighted Regression Smoother (LOESS) procedures that split a time series into three components: trend, season and remainder. For a detailed description of the algorithm see Cleveland et al. (1990). For the sake of comprehension, hereafter we will refer to season, trend and remainder assuming the following meaning:

- **"Season"** as the component obtained that represents exclusively the positive and negative peaks of the detected seasonal cycles within the year.
- **"Trend"** as the component extracted from the time period that only takes into account the inter-annual evolution throughout the same, disregarding seasonal cycles.
- **"Remainder"** as the component that is left over from the two previous ones, and which therefore can be understood as anomalies or extreme events (both exceptionally high and low values) that are outside the average values of the trend and seasonal time series.

1.1.2. Spatial-temporal associations at regional level

Our first objective was to determine the extent to which weather controls intra-annual (seasonal) fluctuations of fire activity. To answer this question we conducted a cross-correlation (CC) analysis at a regional level using the season component from STL. Cross-correlation is a standard method that estimates the degree of similarity between two discrete time sequences (*x* and *y*) as a function of the displacement (lagged or the delay in the synchrony of two temporal events) of one relative to the other (Venables and Ripley, 2002). We followed the formula (1 and 2) about the definitions of the lags established by Venables and Ripley (2002) who extended to several time series observed over the same interval:

$$\gamma_{ij}(t) = \mathrm{cov}\,(X_i\,(t+T), X_j\,(T)) \quad (1)$$

$$c_{ij}(t) = \frac{1}{n}\sum_{s=\max(1,-t)}^{\min(n-t,n)}[X_i\,(s+t) - \overline{X_i}\,][(X_j(s) - \overline{X_j}) \quad (2)$$

Where are X_i and X_j are the two different time series, t is a particular observation, T is the whole time series, s is the scale estimator, c is the correlation or covariance of these observed pairs. In this case, autocorrelation is not symmetric in t for $i \neq j$.

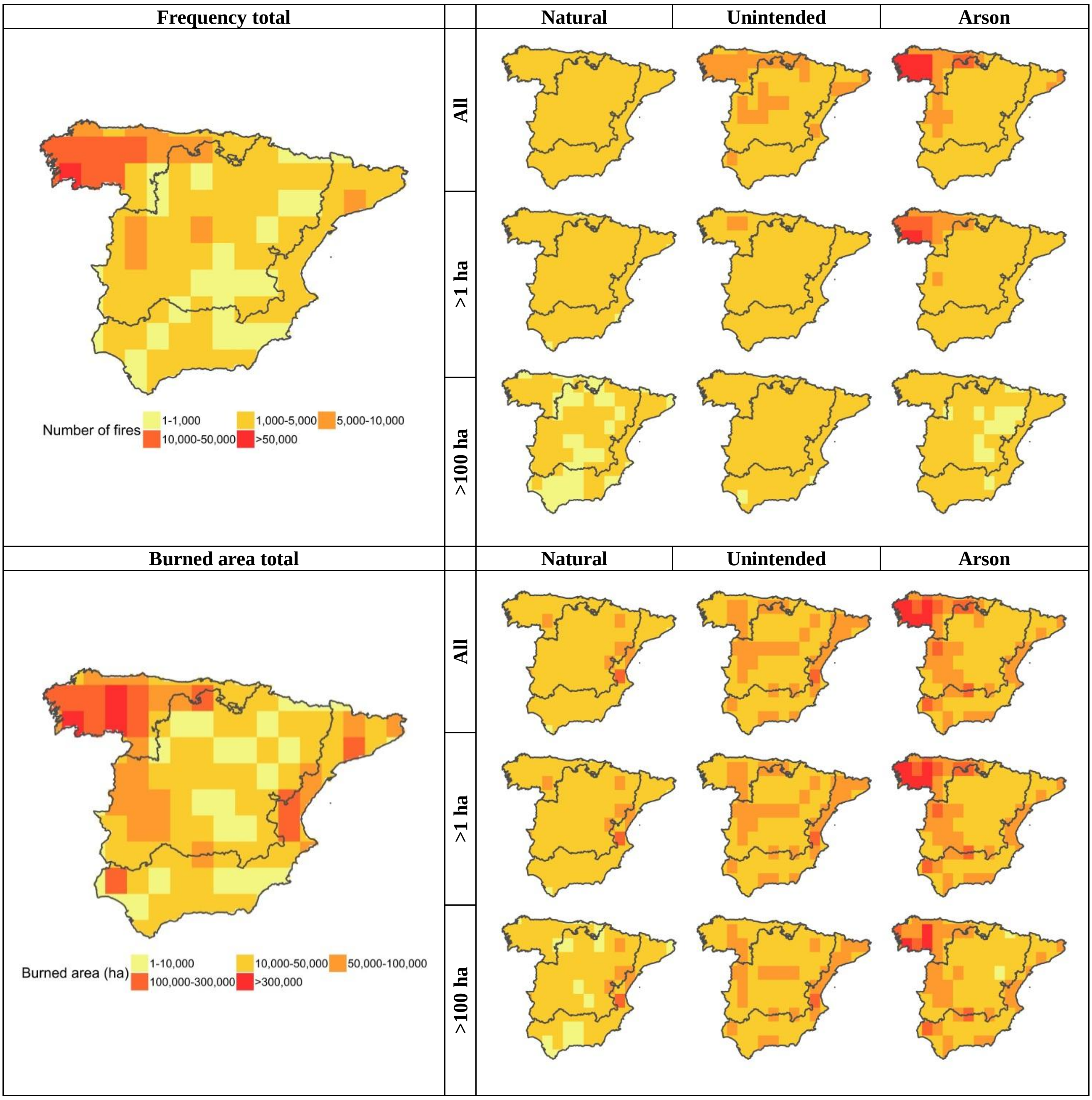

Figure 3. Spatial distribution of total number of fires (top) and total burned area (bottom) across size-and-cause subsets.

In our context, we were seeking the association between time series of fire activity (y) related to past lags in each fire danger index (x). A set of 4 lags (0, 1, 2 and 3 months) was established as the maximum time window of weather influence.

With the purpose of assessing inter-annual dynamics of fire activity and FWI, BI and FFDI, we applied the Mann-Kendall test (MK) coupled with Sen's slope (SS); this combination allows us to identify statistical significant trends and quantify the magnitude of the change. MK is a non-parametric statistical test suitable for identifying trends in times series (Kendall, 1975; Mann, 1945). This test contrasts the null hypothesis (H_0) and alternative hypothesis (H_1) of non-existence or existence of trend, respectively. MK outputs are the τ value, whose value determine the sign of the trend (upward: $\tau > 0$; downward $\tau < 0$); in turn the significance level of the test identifies significant trends (p-value <0.05). Then, we evaluated the magnitude of the changes by means of SS (Sen, 1968). SS is also a non-parametric procedure that estimates the median slope by joining all pair-wise combinations of observations.

1.1.1. Local correlation analysis and mapping

To identify spatial patterns in fire-weather associations, we applied correlation analysis at pixel level by means of the Pearson's R correlation coefficient (Best and Roberts, 1975; Hollander and Douglas, 1973). Pearson's R is a parametric statistical test that indicates the extent to which two variables are linearly related. The test requires at least one of the variables to be normally distributed; in our case, the three fire danger indexes (FWI, BI and FFDI) fulfil this requirement. Pearson's R ranges between +1 and −1, where 1 is perfect positive linear correlation, 0 is no linear correlation, and −1 is negative linear correlation. We calculated and mapped Pearson's R at grid level for each fire-activity subset (Figure 3) reporting the R correlation coefficient and its statistical significance (p<0.05). The process was repeated using each weather index.

2. Results

2.1. Relationships between fire weather danger and fire activity

Figures 4 and S1-S2 (Appendix) show the temporal evolution of the FWI-BI-FFDI (respectively) and fire features at regional level. Generally speaking, the connection between fire danger indices and fire features is noticeable. For instance, fire frequency in the Hinterland and Northwest region closely follows the temporal fluctuation of fire danger whereas the Mediterranean greatly differs since the mid-90s.

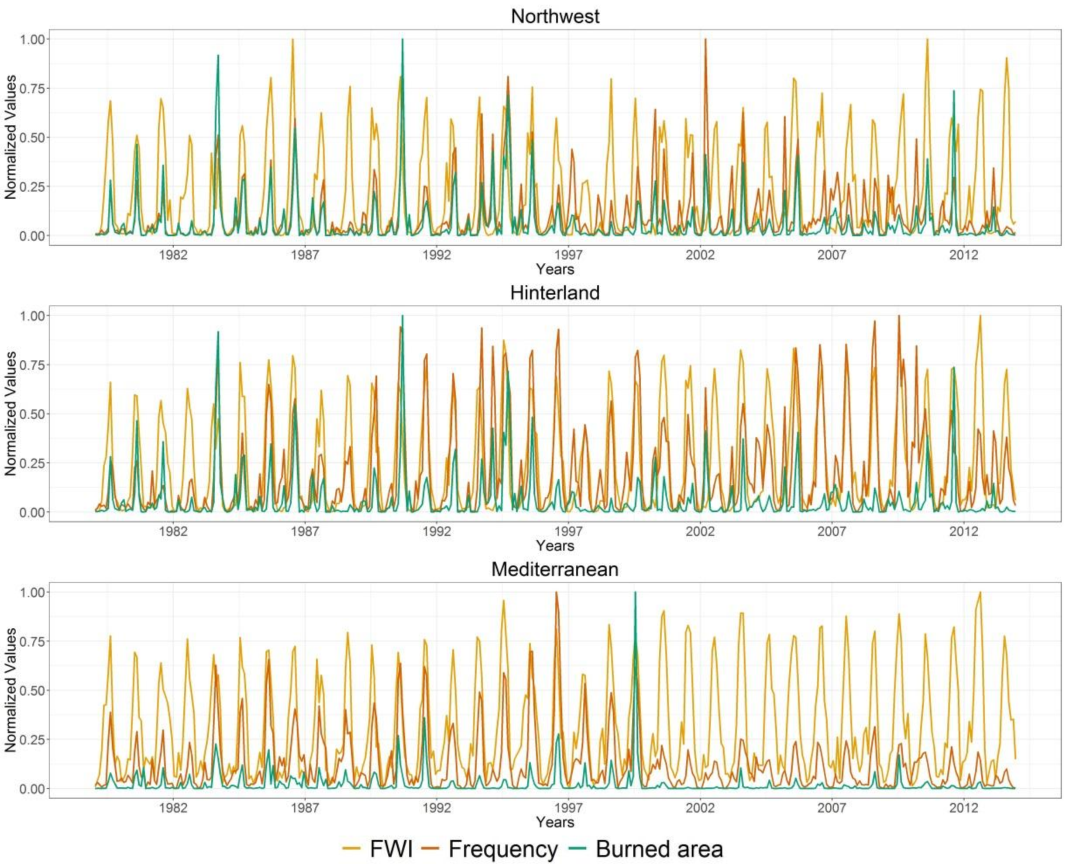

Figure 4. Time series of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

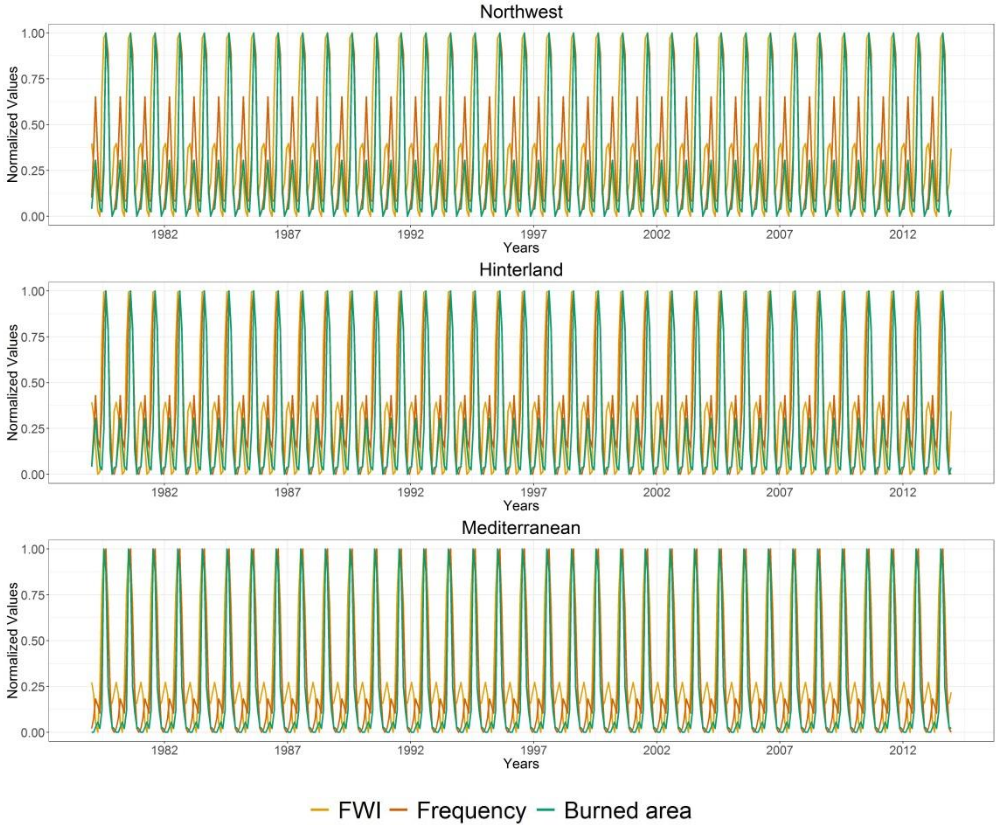

Figure 5. Time series of seasonal component of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

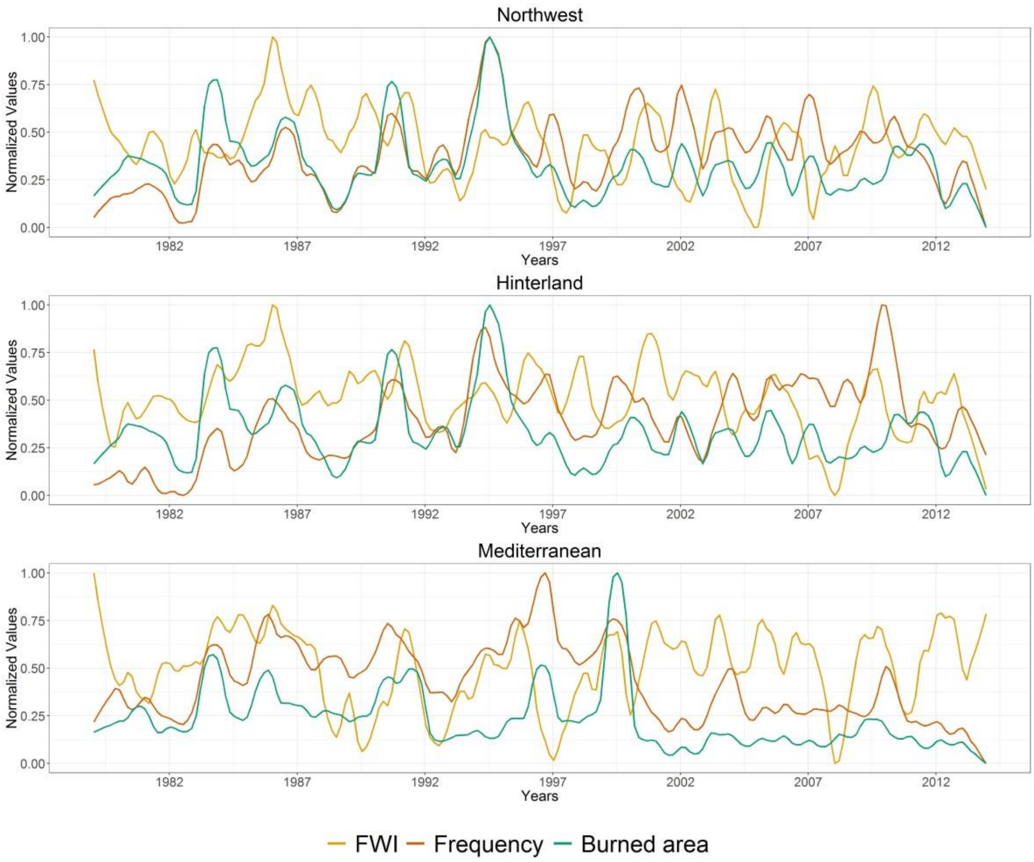

Figure 6. Time series of trend component of FWI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

The seasonal decomposition of fire activity reveals a secondary peak in late winter-early spring particularly noticeably in the Northwest region for fire frequency (Figures 5 and S3-S4 Appendix). However, as we move towards the Mediterranean region, the magnitude of this secondary peak decreases. In turn, the trend component of fire danger has been progressively increasing in all regions (Figures 6 and S5-S6 Appendix). Nonetheless, fire activity shows different tendencies depending on the region. The Northwest region is the most stationary, although during the last decade fire features depict a downward trend. The Hinterland region showed an increase until 2010, decreasing afterwards. In the case of Mediterranean, this decline is also present since 2000.

Table 2. Cross-correlation coefficients between seasonal plus random effects components of FWI, BI and FFDI by monthly lags (-3, -2, -1 and 0) and fire frequency and burned area by region (NW: Northwest, HL: Hinterland and MED: Mediterranean).Fire features were log-transformed and normalized before the analysis.

		FWI				**BI**				**FFDI**			
Region	**Fire feature**	**Lag -3**	**Lag -2**	**Lag -1**	**Lag 0**	**Lag -3**	**Lag -2**	**Lag -1**	**Lag 0**	**Lag -3**	**Lag -2**	**Lag -1**	**Lag 0**
NW	Frequency	-0.27	**0.10**	**0.36**	**0.38**	-0.29	0.02	**0.33**	**0.40**	-0.27	0.05	**0.32**	**0.41**
	Burned area	-0.25	**0.10**	**0.36**	**0.38**	-0.28	0.01	**0.31**	**0.39**	-0.24	0.06	**0.32**	**0.40**
HL	Frequency	-0.26	**0.20**	**0.55**	**0.64**	-0.28	**0.15**	**0.50**	**0.61**	-0.24	**0.20**	**0.55**	**0.65**
	Burned area	-0.23	**0.11**	**0.36**	**0.35**	-0.26	**0.10**	**0.38**	**0.38**	-0.22	**0.10**	**0.35**	**0.36**
MED	Frequency	-0.15	**0.29**	**0.63**	**0.73**	-0.21	**0.22**	**0.57**	**0.64**	-0.19	**0.24**	**0.62**	**0.75**
	Burned area	-0.08	**0.30**	**0.62**	**0.70**	-0.17	**0.21**	**0.55**	**0.64**	-0.12	**0.26**	**0.61**	**0.72**

Results from cross-correlation support and complement the aforementioned seasonal performance. We detect a generalized and strong positive association between seasonal fire activity and fire danger indices (Table 2). Overall, correlations are statistically significant in lags 0 and -1, decreasing and losing significance as lag increases. Correlations in N are usually greater than in BA, and higher in FWI than in BI-FFDI; although regional dissimilarities do exist. The MED region shows the highest correlations for FFDI ($N_{lag=0}$=0.75, $N_{lag=-1}$=0.62; $BA_{lag=0}$=0.72, $BA_{lag=-1}$=0.61) followed by HL ($Nl_{=0}$=0.65, Nl=-1=0.55; $BA_{l=0}$=0.36, $Ba_{l=-1}$=0.35). The most streaking result from this analyses is the moderate correlation values observed in the NW region for FWI ($N_{l=0}$=0.38, $N_{l=-1}$=0.36; $BA_{l=0}$=0.38, $BA_{l=-1}$=0.36). This fits the expected behavior of the region given its secondary occurrence peak in fire incidence during winter related to agricultural burnings.

One of the most remarkable findings is the consistent positive trend of FWI-BI-FFDI across regions, thus mainland Spain experiences increased fire weather potential over time. Nonetheless, fire activity performs differently across regions (Table 3). Fire frequency shows significant and positive trends only in NW and HL, more intense in the NW region (SS 0.49 *vs.* 0.20). On the contrary, fire occurrence in the MED region tends to decay. Burned area displays non-significant trends in all the study regions excluding MED, with a significant negative trend. Hence, it is obvious that the evolution of fire activity differs from the one by FWI-BI-FFDI in most of the study area. This is noticeable in the disconnection of fire danger indices and fire activity in the Mediterranean after the 90s (Figures 4 and S1-S2 Appendix). Therefore, short-term weather conditions have limited ability to control dynamics in fire activity other than seasonal cycles, at least at global/regional level. In general, fire danger seems to be more related to intra-annual cycles of fire activity while has a limited influence on long-term trends.

Table 3. Mann-Kendall coefficients Tau and Sen's slope output of trend component of the decomposed time series of FWI, BI and FFDI, fire frequency and burned area in each region. Significant cases (p value < 0.05) are denoted by an asterisk. Only burned area was log-transformed and normalized before analyses.

	Northwest		**Hinterland**		**Mediterranean**	
Fire feature	**Tau**	**Sen's slope**	**Tau**	**Sen's slope**	**Tau**	**Sen's slope**
FWI	0.31*	0.001	0.49*	0.001	0.39*	0.001
BI	0.36*	0.001	0.52*	0.001	0.39*	0.001
FFDI	0.40*	0.001	0.58*	0.001	0.46*	0.001*
Frequency	0.24*	0.49*	0.36*	0.20*	-0.28*	-0.13*
Burned area	0.01	0.00	0.02	0.00	-0.39*	-0.01*

2.2. Differences between fire danger indices by fire feature and fire-activity subset

At a first glance, regarding local level, the association of fire activity with weather indices is greater in the seasonal component and, in general, stronger for fire frequency than for burned area. This is inferable from the higher value of the correlation coefficients and the larger number of significant locations we found. Overall, fire danger indexes are better linked to fire ignition source than fire size; however, differences were detected in terms of spatial patterns and also depending on the ignition source or the final area of the fires. Additionally, the remainder component is usually more correlated with human caused fires above 1 ha. In turn, the spatial patterns observed across fire weather danger rating indices resemble one another, depicting a similar picture when comparing either components of time series or fire-activity subsets (Figures from S7 and S8 Appendix). In any case, BI (Figures 7 and 8) seems to provide more insightful outputs in terms of Pearson's coefficients and spatial patterns, not only in the seasonal component as well as in the trend component. On the other hand, the others fire danger indices (FWI and FFDI) show similar average Pearson's R (Figures S9 and S10 Appendix).

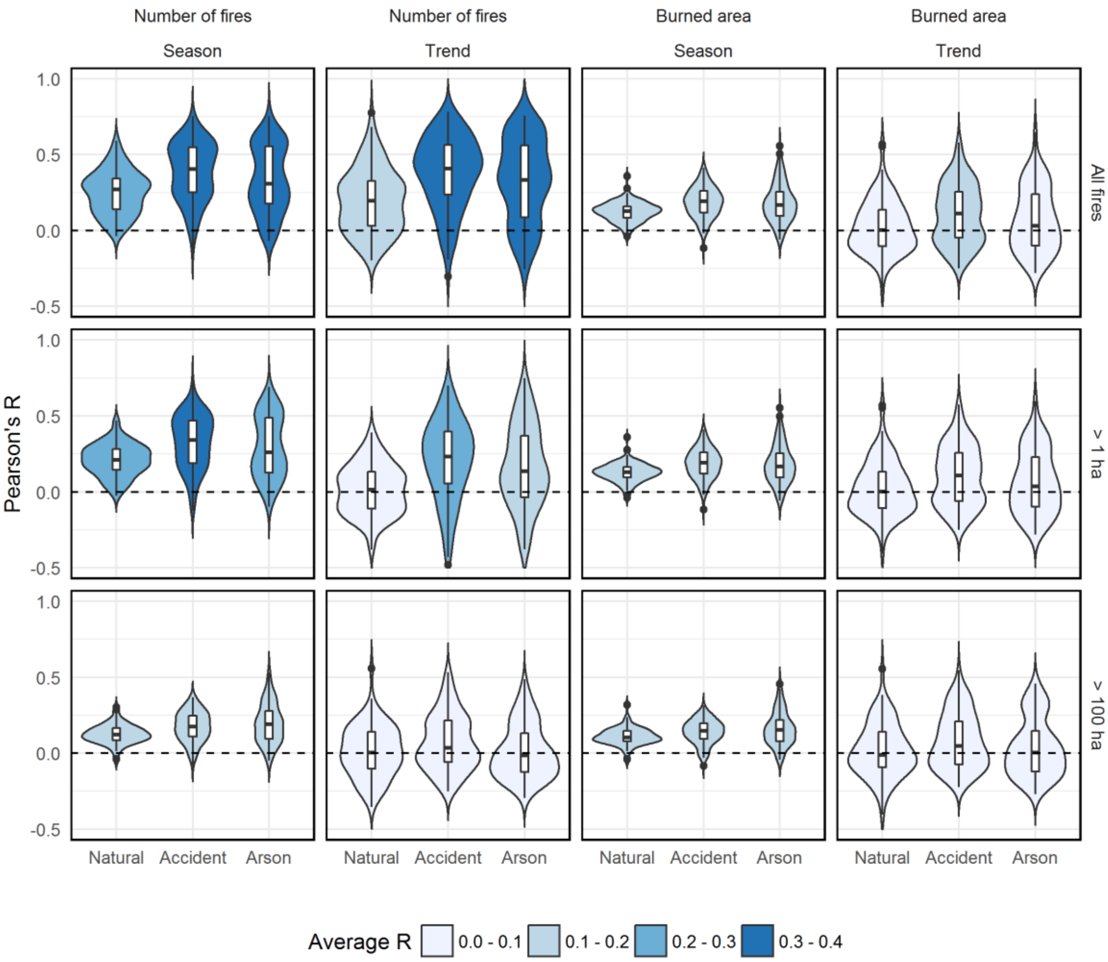

Figure 7. Statistical distribution of the Pearson's R between total number of fires-burned area and BI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend).

At a seasonal level, significant correlations were found in the whole study area regardless of the fire-activity subset or fire feature. However, natural-caused fires portray a more homogenous pattern compared to those triggered by a human-related source. R's values in natural fires are consistently higher and positive, whereas we observe spatial gaps of low (and even negative) correlation values in the central North and East area in the case of anthropogenic fires, especially in arson fires. This pattern is not observed in large fires, which tend to be positively related at seasonal level irrespective to the source of ignition.

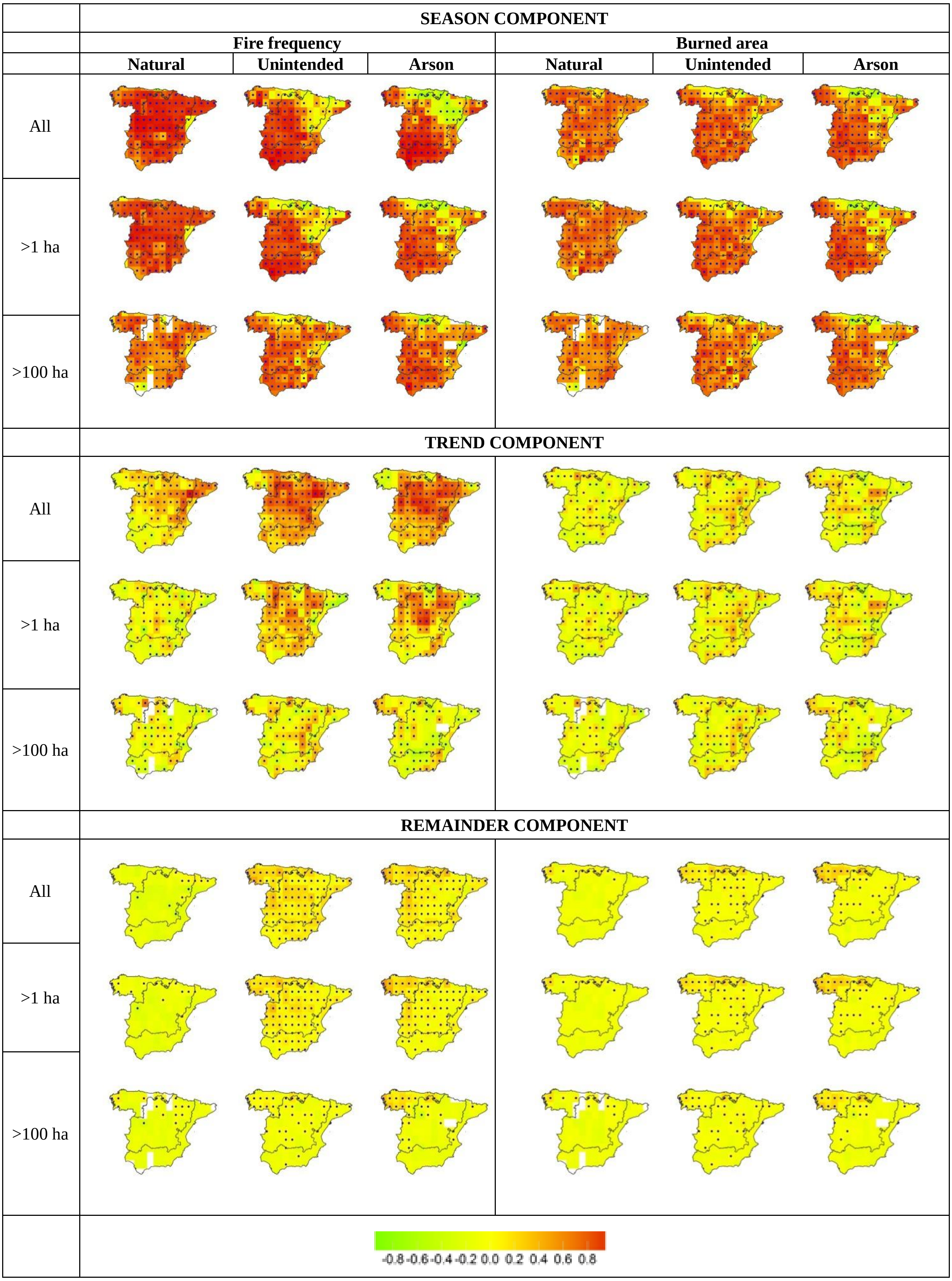

Figure 8. Spatial pattern of Pearson coefficients between BI *vs*. seasonal, trend and remainder components of fire frequency (left) and burned area (right). Green to yellow values indicate negative association; yellow to red indicate positive association. Points mark significant relationships ($p<0.05$). Blank pixels indicate no-fire activity in the subset.

The trend component performs differently, displaying contrasting situations across fire-activity subsets. Overall, burned area shows weak association with fire weather indices, even though significant values area detected. In that regard, more than 40% of the significant locations display negative associations, suggesting poor influence of weather over burned area trends. The yearly evolution of natural fires seems to be slightly linked to weather trends in the Northeastern end but only in the case of the number of small fires. Correlation values in the remaining fire-activity subsets of natural fires are, on average, below the 0.46 threshold in the case of fire frequency and 0.17 in burned area. Nonetheless, locations within the Hinterland and Mediterranean regions display significant and positive correlations in the case of frequency of small-to-medium human-caused fires. The effect of size over trend correlations is fairly sturdier than in the seasonal component; correlation values decrease as fire size increases, as is noticeable in both unintended and arson fires.

Finally, the remainder component –which maybe ultimately linked to extreme events or anomalies – shows moderate to low correlation values no matter the subset. However, the most outstanding result is the occasional existence of positive and significant associations in some fire-activity subsets. These are more noticeable and widespread in fire frequency than in burned area. If we focus on all fires or those above 1 ha burned, the association is found significant elsewhere in terms of number of fires. If we only account for large fires, then significant relationships are limited to the Northwest region. This pattern is also observed in the case of burned area, but in this case significant locations are only observed in central and Northwest Spain.

3. Discussion

In this study we explored time-based associations among fire weather danger rating indices and two of the most important fire regime features (i.e. fire frequency and burned area) at regional and local level. This enabled us to understand the diverse contribution of weather conditions to fire incidence by regions, whereas we delve into the detail of the spatial-local distribution of associations depending on fire size and ignition cause.

Our results underline a desynchronize of fire-weather and fire regime in the Mediterranean region since 1994. The reasons that might be explain this aspect is to be linked to a change in firefighting policy such France (Curt and Frejaville, 2018; Fréjaville and Curt, 2015). At the same time, fire danger conditions show a general growth, which has been reported over large forest areas over European Mediterranean countries (Moriondo et al., 2006), due to the rising frequency of years with high fire risk, the longer fire danger season and the greater likelihood of extreme events.

Generally speaking, we observe a close association between short-term (up to 2 months) weather conditions and seasonal cycles of fire activity. The association is stronger in fire frequency than burned area and in the case of BI than in the rest of indexes, although with slight regional differences (Figures S1 and S2, Appendix). For instance, in the case of fire frequency the correlation is higher in the Hinterland and Mediterranean regions (Jiménez-Ruano et al., 2017b) while the Northwest displays moderate seasonal correlations; likely due to the secondary peak of fire incidence during winter months linked to human activities in the last (Moreno et al., 2014; Sousa et al., 2015). It is worth noting that this region accounts for 75 % of arson fires, especially to remove scrub for obtaining pasture for livestock or to reduce stubble (Moreno, 2016). As we expected, CC outputs (Table 2) pointed out that fire weather danger conditions have a remarkable association during the ignition month –lag 0– that weakens towards a month before –lag -1–, although remaining statistically significant.

On the other hand, the temporal evolution expressed as the trend component performs differently. Fire weather indices display significant increasing trends all over the study area (Jolly et al., 2015). In the same line, increased fire occurrence in the Northwest region of mainland Spain (Jiménez-Ruano et al., 2017a) and growing tendency towards severe fire-prone situations in the inland region have already been documented (Martínez et al., 2009; Trigo et al., 2016). Thus, we may conclude that fire frequency tends to increase over time, both in areas where there was already a high incidence and in areas where there was less, so that fire activity becomes spatially more extensive (Moreno, 2016). However, the Mediterranean region seems to behave otherwise, with an overall decrease both in fire ignitions and affected area (Jiménez-Ruano et al., 2017a; Turco et al., 2016). Our findings suggest that, to some extent, trends in fire frequency in the central and north regions are connected with the inter-annual evolution of fire weather indices, except in the case of large fires. On the other hand, the Mediterranean region is somewhat desynchronized from the overall increasing trend of fire weather indices, particularly clear since the 90s (Figure 4). Furthermore, dynamics in burned area do not appear to be as strongly linked to weather as ignition does. In this sense, it is well-known that fire activity in the Mediterranean region is controlled by longer periods of high temperatures and/or lower fuel moisture (Rivas

Soriano et al., 2013). In fact, fire weather conditions represent around 25% of the influence over the spatial distribution of fires in other Mediterranean environments such as the south of France (Ruffault et al., 2017). In contrast, in the south Alps, in the late 20th century the climate influence is decreasing in favor of human activities and fuel availability (Zumbrunnen et al., 2009). According to our findings, this effect is limited to the intra-annual (seasonal) cycles of fire activity but not connected to the inter-annual evolution, i.e., warm and dry periods during summer promote fire incidence but warmer conditions along the years do not favor further fire activity.

The spatial disaggregation of correlation exposed local underlying patterns of association. Again, the link is stronger in seasonal cycles than in temporal evolution, and weaker in burned area compared to fire frequency. Overall, weather conditions influence fire ignition to a higher extent than burned area size. Fire propagation is a more convoluted process involving a number of factors both environmental –fuel load or landscape structure– or anthropogenic –fire suppression (Koutsias et al., 2012; Krebs et al., 2010; Liu et al., 2012; Liu and Wimberly, 2016). On the other hand, accounting for the ignition source or the final size of the fire allows more insightful analyses. In fact, the proportion of small fires has been increasing from the period 1974-1993 and today they remain stable at these high percentages, around 70% (Jiménez-Ruano et al., 2017a; Moreno, 2016). Furthermore, addressing human-related fires separately allowed us to identify spatial gaps of correlation with fire weather indices such as those in fire frequency in the central north area of the country. In this sense, it is well-known that in some locations of the NW, fires are triggered by arsonists taking advantage of dry-warm weather situations (Prestemon et al., 2012), which can ultimately become uncontrolled depending on the fire-fighting capability and availability (Fuentes-Santos et al., 2013).

Seasonal variations in burned area from human-related fires are greatly related to weather conditions, more markedly in the Northwest of mainland Spain. This result is consistent with the work by Trigo et al. (2016), who highlighted the western half of the Iberian Peninsula as more susceptible to large wildfires. Furthermore, unintended fires are also significantly associated to fire weather danger in the north-central and east region. In this sense, Badia et al. (2011) have detected an increase in fire danger in Catalonia explained by mean maximum temperature in July in both scrublands and coniferous forests. In that regard, those indices accounting for fuel moisture (BI and FWI) produce higher correlations and more contrasted spatial patterns than those purely meteorological (FFDI). In contrast, Jiménez-Ruano et al. (2017b) reported a decrease in frequency and burned area for wildfires above 500 ha, likely explained by the improvement in fire suppression investment over the years.

Different local associations were detected in the trend component. The most interesting outcome was found in locations with negative associations between fire weather and fire activity, especially in a number of locations along the Mediterranean coast. Overall, positive associations are expected, i.e., higher fire danger should lead to more fire activity; but the existence of such negative associations suggests that the inter-annual evolution of fire incidence is not fully controlled by weather. This was already observed at regional level in the Mediterranean and also locally in the Northeastern region. However, the HL region brings together some positive correlations with fire weather trends regardless of the cause.

Finally, analyses on the remainder component revealed a certain degree of association between anomalies in fire activity and fire weather indices. This is particularly interesting since these relationships are consistently positive. Thus, there appears to be some connection between random anomalies or extreme events.

However, our work has some shortcomings that should be mentioned. Firstly, the quality of the dataset used in the analysis could be improved in terms of resolution spatial. Secondly, it would be interesting to combine meteorological variables and fire indices to build better models, while improving their predictive power. In this sense, we can find some examples in De Angelis et al., (2015) who have been able to enhance the performance with a Maxent approach. On the other hand, care should be taken with the indiscriminate use of FWI, since in some areas of Italy it has been observed that FWI probably overestimates fire danger, especially during early spring and autumn (Giannakopoulos et al., 2012). Thus, it seems reasonable to move towards a fine tuning of the existing indices, depending on the analyzed environment.

5. Conclusions

In this work we investigate the association between fire danger indices and two of the most common fire regime features, such as number of fires and burned area, in mainland Spain. We have accounted for all fire records in the period 1979-2013 in order to explore the joint influence of FWI, BI and FFDI at regional level, as well as analyzing their own contribution separately at local level.

Our findings suggest that weather conditions control intra-annual (seasonal) cycles of fire activity but have a limited influence on long-term trends. Overall, fire danger is better linked to fire ignition than burned area size, although differences were detected in terms of spatial patterns and also depending on the ignition source or the ultimate size of the fires.

According to cross-correlation outputs, the seasonal influence of weather is stronger during the first two months before the fire, although in some regions such as the Hinterlands it remains statistically significant up to three months. Seasonal burned area correlation outputs seem to be more associated to arson cause in the Northwest, the most fire affected and arson-related region. The assessment of the trend component points towards the independence of fire activity in the Mediterranean losing synchronicity with fire weather danger since 1994. Altogether, it suggests that human factors have taken over weather conditions. In cross-correlations analysis, both FWI and FFDI were considered useful fire indices due to its good performance at regional level while FWI is widely used in the bibliography.

At local level, the comparison of fire weather indices promotes BI as the best suited to analyze fire-weather relationships in the context of mainland Spain due to its higher correlations values. In addition, it seems to work quite well for the seasonal and trend components of burned area.

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SUPPLEMENTARY MATERIAL

The role of short-term weather conditions in temporal dynamics of fire regime features in mainland Spain

Adrián Jiménez-Ruano, Marcos Rodrigues Mimbrero, W. Matt Jolly and Juan de la Riva Fernández

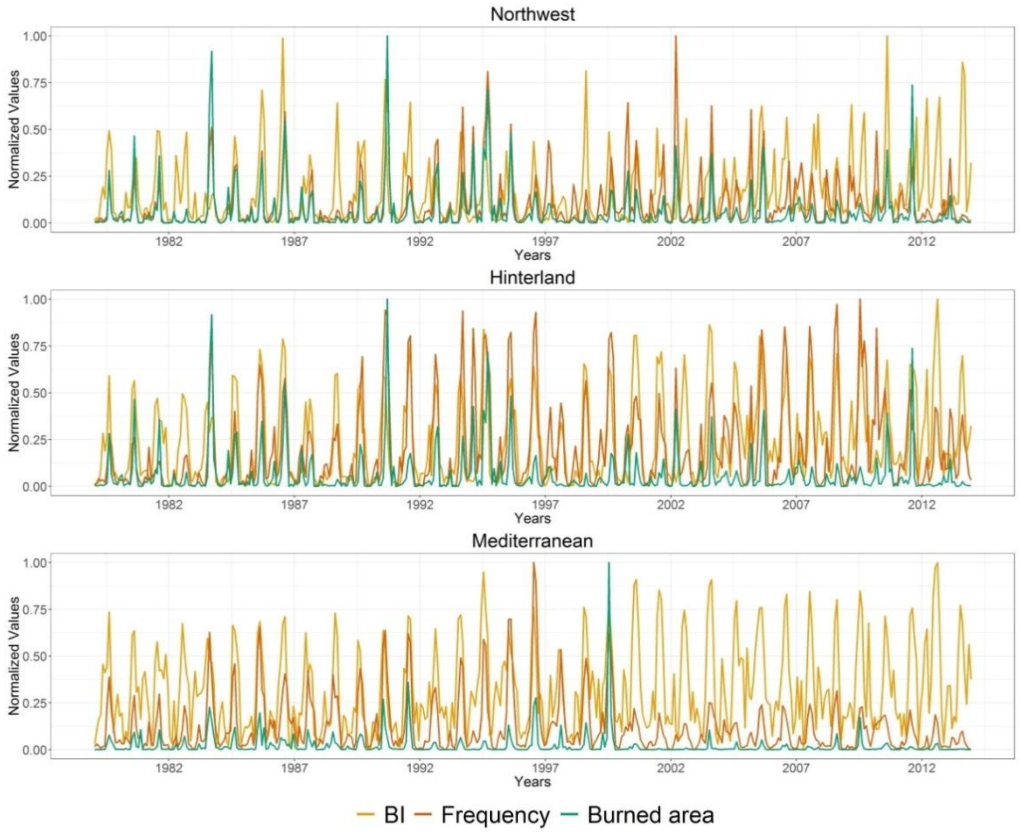

Figure S1. Time series of BI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

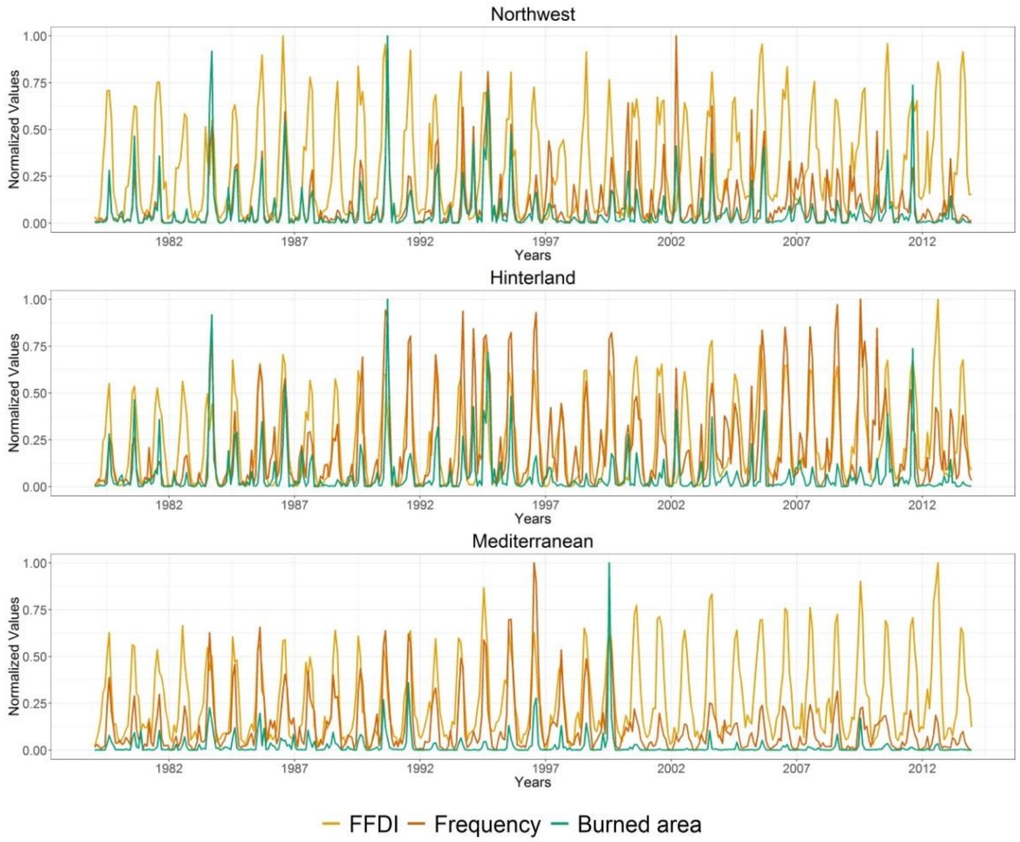

Figure S2. Time series of FFDI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

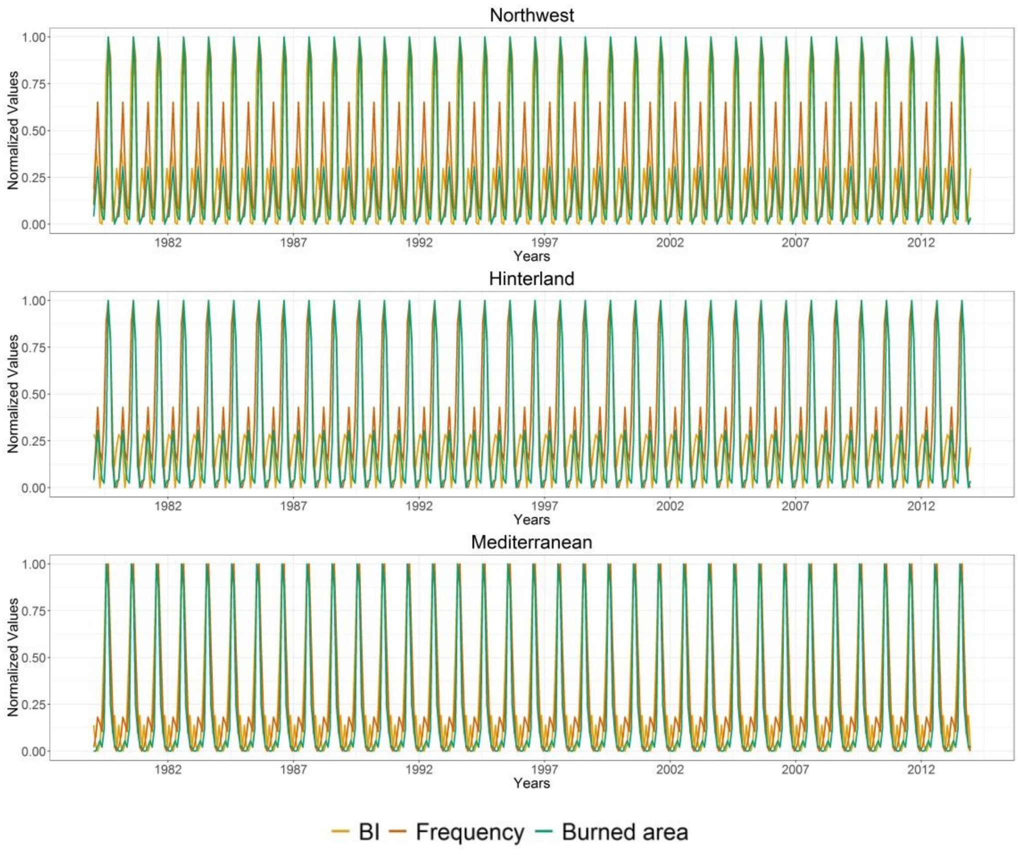

Figure S3 Time series of seasonal component of BI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

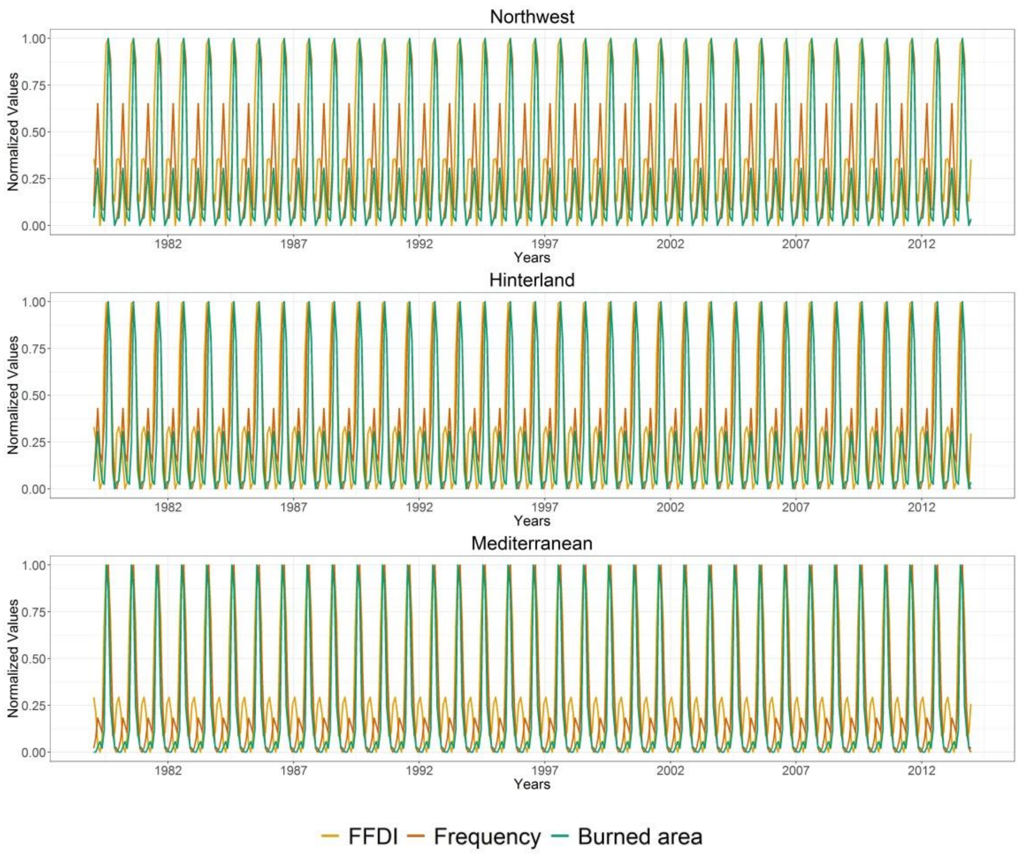

Figure S4. Time series of seasonal component of FFDI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

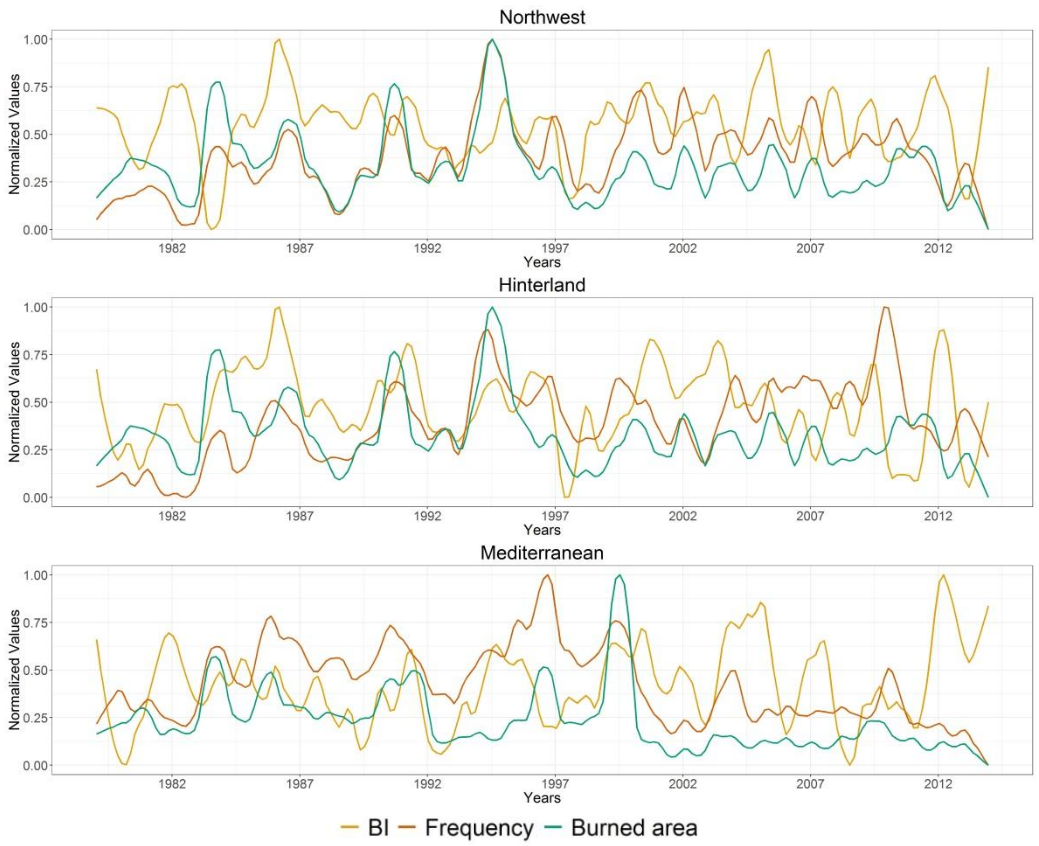

Figure S5. Time series of trend component of BI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

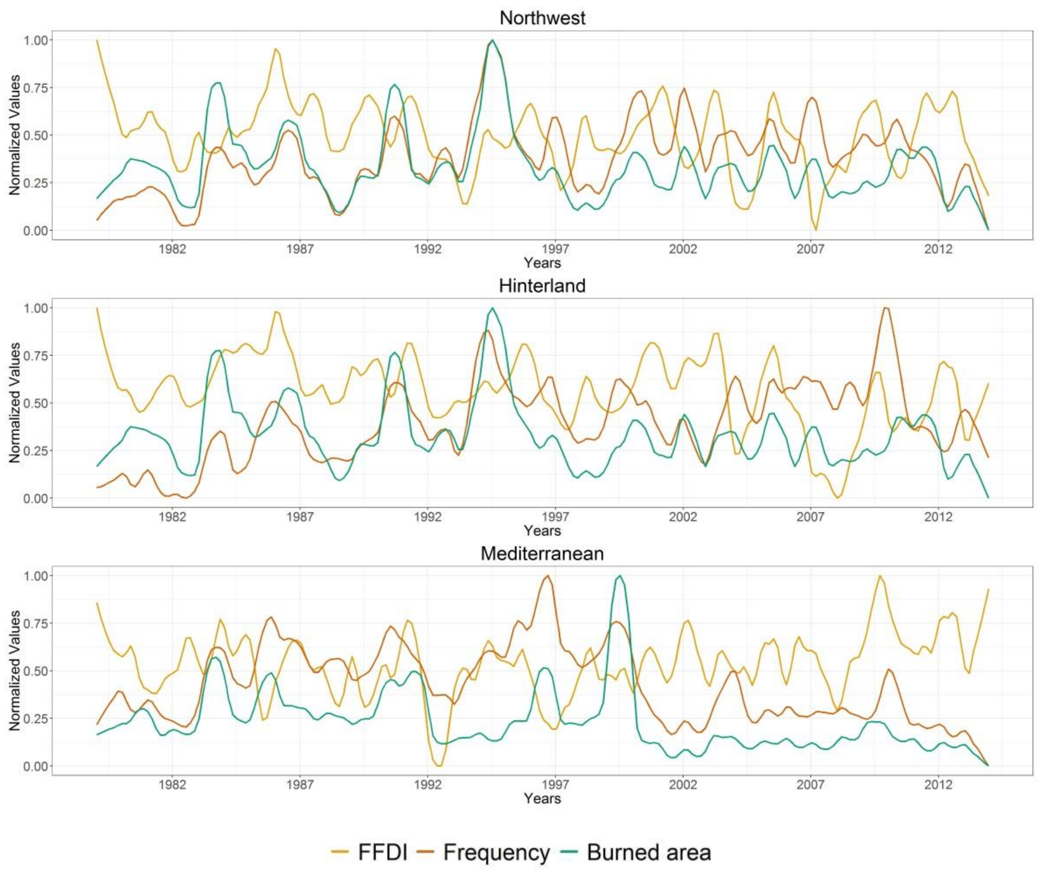

Figure S6. Time series of trend component of FFDI (yellow line), fire frequency (red line) and burned area (green line). All variables are normalized into a 0-1 range.

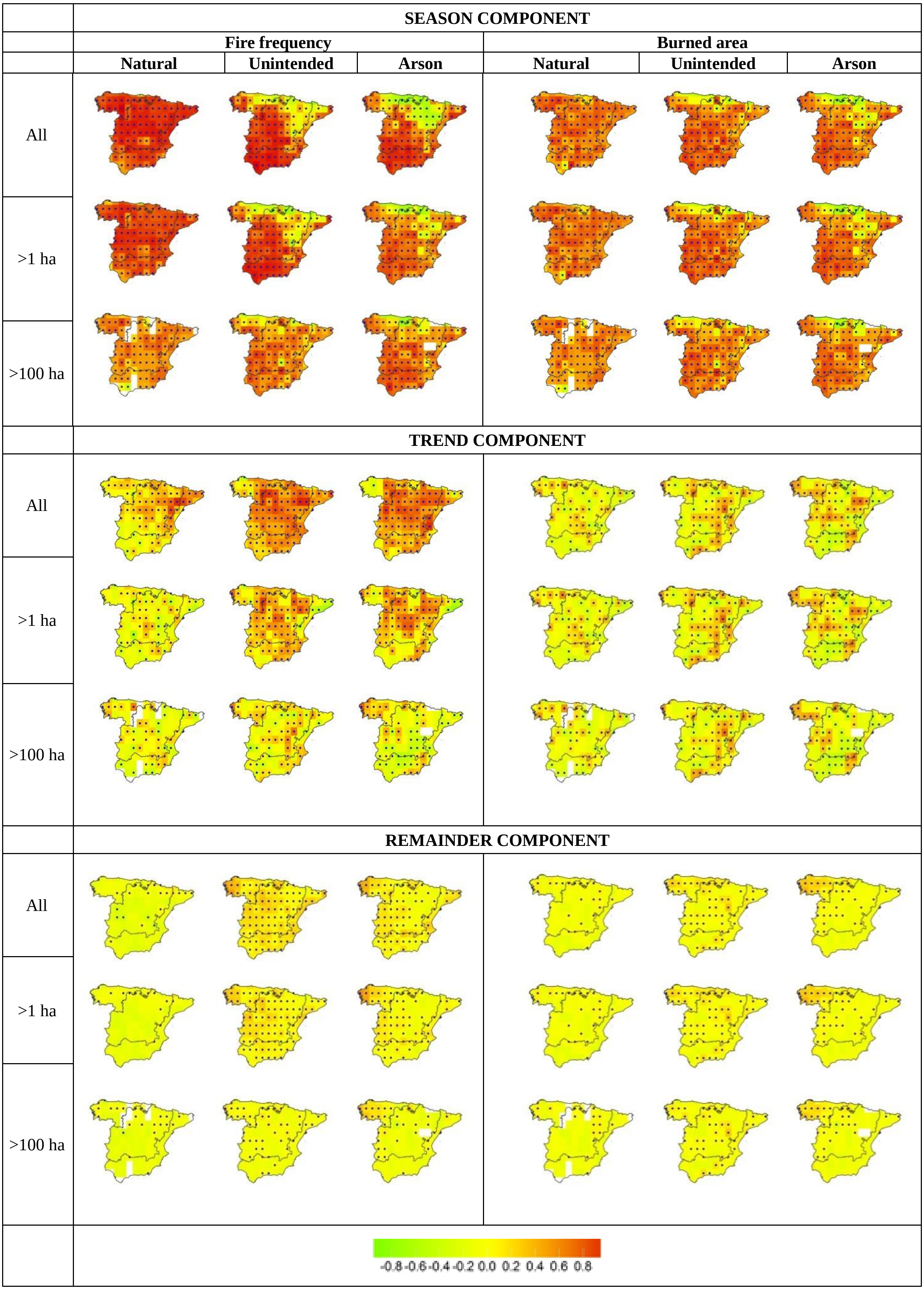

Figure S7. Spatial pattern of Pearson coefficients between FWI *vs*. seasonal, trend and remainder components of fire frequency (left) and burned area (right). Green to yellow values indicate negative association; yellow to red indicate positive association. Points mark significant relationships (p<0.05). Blank pixels indicate no-fire activity in the subset.

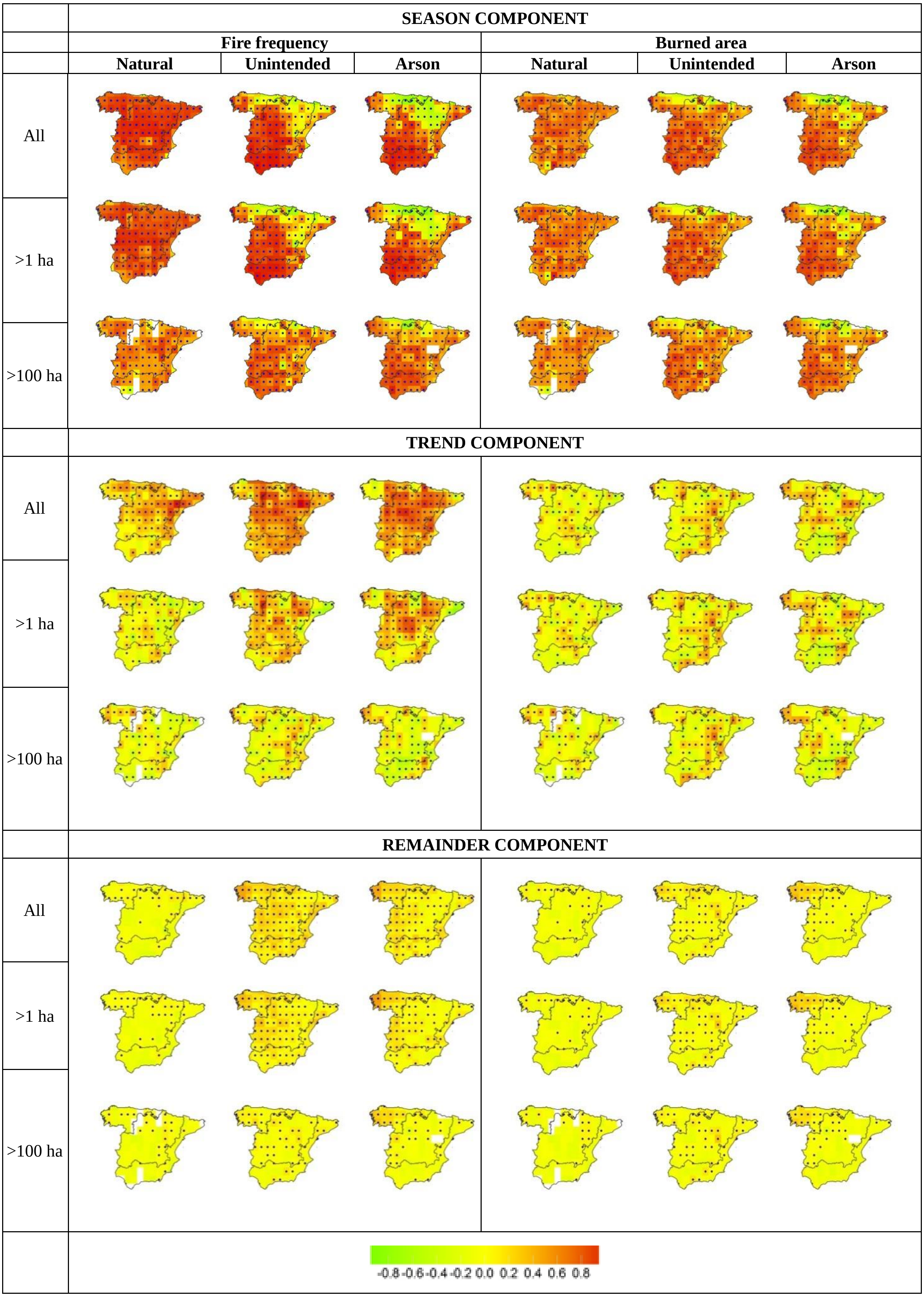

Figure S8. Spatial pattern of Pearson coefficients between seasonality, trend and remainder components of fire frequency-burned area vs. FFDI. Green to red gradient indicates relationships from negative to positive. Points indicate significant relationships for p value <0.05. Blank pixels indicate no contribution to the scenario.

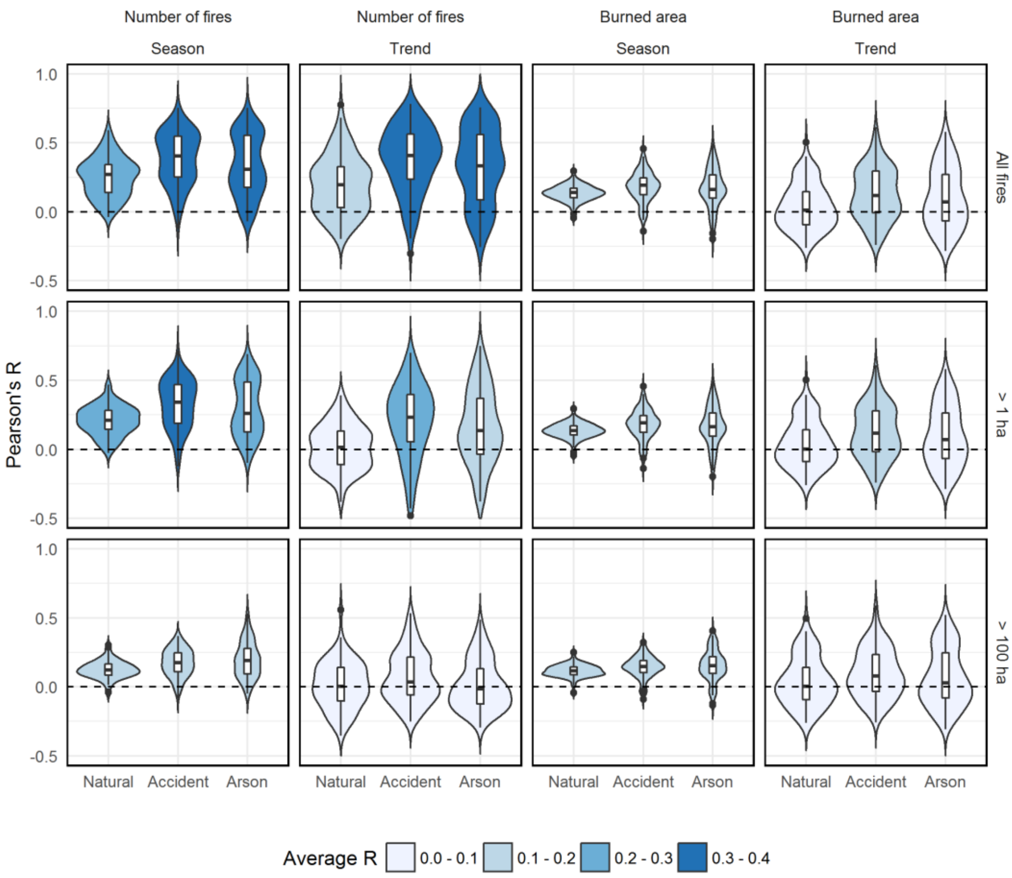

Figure S9. Statistical distribution of the Pearson's R between total number of fires-burned area and FWI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend).

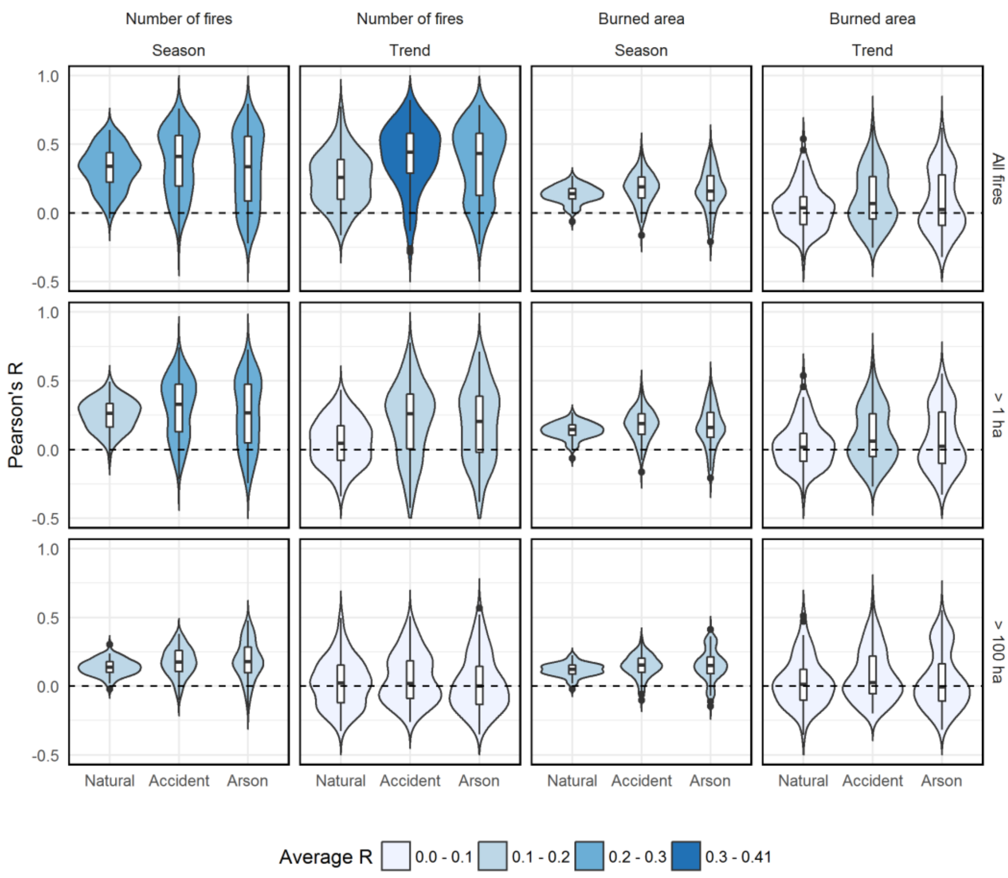

Figure S10. Statistical distribution of the Pearson's R between total number of fires-burned area and FFDI. Blue gradient categories show the average of Pearson's R of pixels in each fire size-cause subset and component (season and trend).