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Uncovering current pyroregions in Italy using wildfire metrics

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Abstract

Background: Pyrogeography is a major field of investigation in wildfire science because of its capacity to describe the spatial and temporal variations of fire disturbance. We propose a systematic pyrogeographic analytical approach to cluster regions on the basis of their pyrosimilarities. We employed the Affinity Propagation algorithm to cluster pyroregions using Italian landscape as a test bed and its current wildfire metrics in terms of density, seasonality and stand replacing fire ratio. A discussion follows on how pyrogeography varies according to differences in the human, biophysical, socioeconomic, and climatic spheres.

Results: The algorithm identified seven different pyroregion clusters. Two main gradients were identified that partly explain the variability of wildfire metrics observed in the current pyroregions. First, a gradient characterized by increasing temperatures and exposure to droughts, which coincides with a decreasing latitude, and second, a human pressure gradient displaying increasing population density in areas at lower elevation. These drivers exerted a major influence on wildfire density, burnt area over available fuels and stand replacing, which were associated to warm-dry climate and high human pressure. The study statistically highlighted the importance of a North–South gradient, which represents one of the most important drivers of wildfire regimes resulting from the variations in climatic conditions but showing collinearity with socioeconomic aspects as well.

Conclusion: Our fully replicable analytical approach can be applied at multiple scales and used for the entire European continent to uncover new and larger pyroregions. This could create a basis for the European Commission to promote innovative and collaborative funding programs between regions that demonstrate pyrosimilarities.

Keywords: Pyrogeography, Affinity propagation, Forest, Mediterranean basin, Clustering

Background

Pyrogeography is a major field of investigation in wildfire science because of its capacity to describe the spatial and temporal variations of fire disturbance (Archibald et al. 2013; Stambaugh et al. 2014; Chaste et al. 2018). Bowman et al. (2013) defined pyrogeography as the discipline that studies the past, current, and future projected distribution of wildfires. It offers new perspectives on landscape wildfire management and the link between wildfires and human health and livelihoods. The appropriate parameters used to characterize the pyrogeography of a territory depend on the specific needs of fire management in a given region and the responses of target ecosystem services to wildfires (Bowman 2015). Basically, pyrogeography can span over a wide variety of temporal and spatial scales, ranging from the local to global extent and from a few years to thousands of years (Krawchuk et al. 2009; Bowman et al. 2011; Roos et al. 2014).

One approach to represent such multi-scaled spatiotemporal interactions is to employ suitable recurring wildfire metrics to group different regions on the basis of their pyrosimilarities (i.e., pyroregions) within a defined space–time window (Morgan et al. 2001; Fréjaville and

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Curt, 2015; Krebs et al. 2010; Williams et al. 2012). Clustering pyroregions provides guidelines for decision makers suggesting which strategies may be most effective for combining wildfire risk reduction with natural resource protection (Syphard et al. 2020). For example, the Landfire project (http://www.landwildfire.gov/, accessed 12 May, 2021) mapped five pyromes as a function of wildfire frequency and severity. The resultant map currently plays a key role in planning wildfire management interventions in the United States (Keane et al. 2007; Keane and Karau 2010). Clustering pyroregions may also be helpful for scientists to assess potential drivers altering fire occurrences and to assess potential future scenarios relative to an appropriate baseline (Keeley et al. 2019; Rodrigues et al. 2019).

Numerous and varied studies have attempted to cluster pyroregions at the global, continental and local scales and for past, current, and future wildfire scenarios, including related driving factors (Conedera et al. 2009; Moreno and Chuvieco 2013; Archibald et al. 2013, for a partial review). Each study applied different clustering methods to estimate pyrosimilarities among regions using historical wildfire data. For example, Archibald et al. (2013) used a Bayesian clustering algorithm to identify global pyromes, while Conedera et al. (2018) characterized the pyrogeography of the Alpine area using a hierarchical cluster analysis based on the Bray–Curtis index and average-linkage method. Syphard and Keeley (2020) identified wildfire ecoregions using a k-means algorithm in California, USA. Parente et al. (2016) identified two different wildfire regime regions in the Iberian Peninsula, using historical wildfire data and climate classification patterns with scan statistics methods for cluster detection.

However, the abovementioned methods denoted some limitations. These methods begin with a random choice of centroids performing different clustering results on different sequences of the algorithm. Therefore, the results may not be repeatable and lack of consistency. In addition, fire management goals might to select a priori how many groups you want to generate, and this is not always possible, especially for data sets of high complexity (Fiaschetti et al. 2021).

To avoid these drawbacks, we employed the Affinity Propagation (AP) algorithm to cluster current pyroregions using wildfire metrics. As stated in the next section this method has numerous advantages over related cluster analyses and the literature denoted a rare use in environmental-related works.

Our study presents a systematic analytical approach to uncover pyroregions on the basis of their pyrosimilarities. The approach is applied as a case study to the entire Italian territory, being a complex region with highly variable landscape features, flammability, urbanization contexts and climate conditions (Ascoli et al. 2020; Elia et al. 2020a). In addition, we discuss how the pyrogeography varies due to differences in the biophysical, socioeconomic, and climatic spheres.

Data and methods

Figure 1 shows the overall workflow of the methods developed for this study.

Study area

The Italian peninsula is located in the heart of the Mediterranean Basin and covers a surface area of approximately 301,330 km^2. It is one of the European regions most affected by wildfires (San-Miguel-Ayanz et al. 2020) with a heterogeneous mix of vegetation and fuel types (Ascoli et al. 2020), and diverse urbanization contexts and weather conditions (Mancini et al. 2018). Twenty-three percent of the peninsula consists of plains, 42% of rolling hills and the remaining 35% of mountain chains (Elia et al. 2020a). The main mountain chains in Italy are represented by the Alps in the North and the Apennines running throughout the peninsula. Given this particular configuration, the climate is characterized by a North–South gradient, ranging from temperate cool to Mediterranean warm. These climatic conditions and the surrounding Mediterranean Sea make this landscape one of the most important hotspots in terms of biodiversity. Forests cover approximately 11 million ha (RAF 2019), 22% of which are located in the Alpine region and the remaining 78% along the peninsula.

Every year Italy experiences a considerable number of wildfire events, with a clear difference in wildfire regime from North to South (Valese et al. 2014; Elia et al. 2020a). Indeed, the Italian peninsula and islands are characterized by very high temperatures and biophysical and socioeconomic heterogeneity, which influence landscape flammability and wildfire ignition patterns with cascading effects on the spatio-temporal variability and impacts of fire disturbance.

To identify the pyroregions in our study, we used the Nomenclature of Territorial Units for Statistics, level 3, (NUTS3) of the European Union (http://ec.europa.eu/eurostat/web/nuts/), which is a standard geocode for referencing the subdivisions of countries for scientific and statistical purposes. Level 3 is the best compromise between the need for homogeneity in wildfire metrics and the administrative unit, where data on socioeconomic variables can be extracted (Conedera et al. 2018). Therefore, our study area included 110 NUTS3 for the whole Italian territory (Fig. 2).

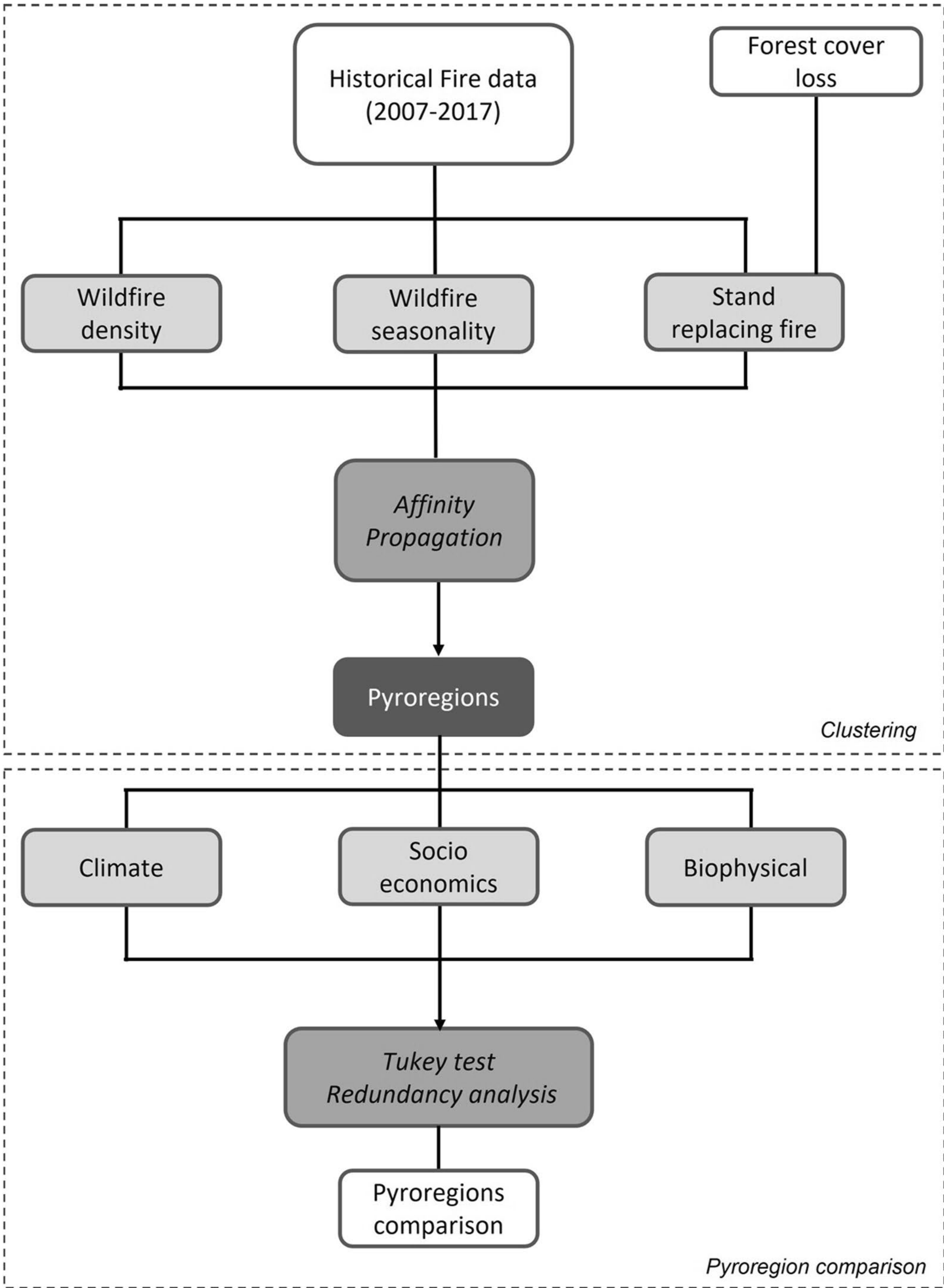

Fig. 1 Block diagram of the proposed pyrogeographic analytical approach

Historical wildfire data set and metrics

The historical wildfire data set was derived from the Comando Unità Forestali, Ambientali e Agroalimentari (CUFA, 'Command of the Forest, Environmental and Agri-food units'), Carabinieri Force, and Forestry Services of Autonomous Regions. This data set corresponds to georeferenced polygons recorded between 2007 and 2017. Although this 11-year data set represents a limited period for clustering regions on the basis of their pyrosimilarities, it is the most harmonized and

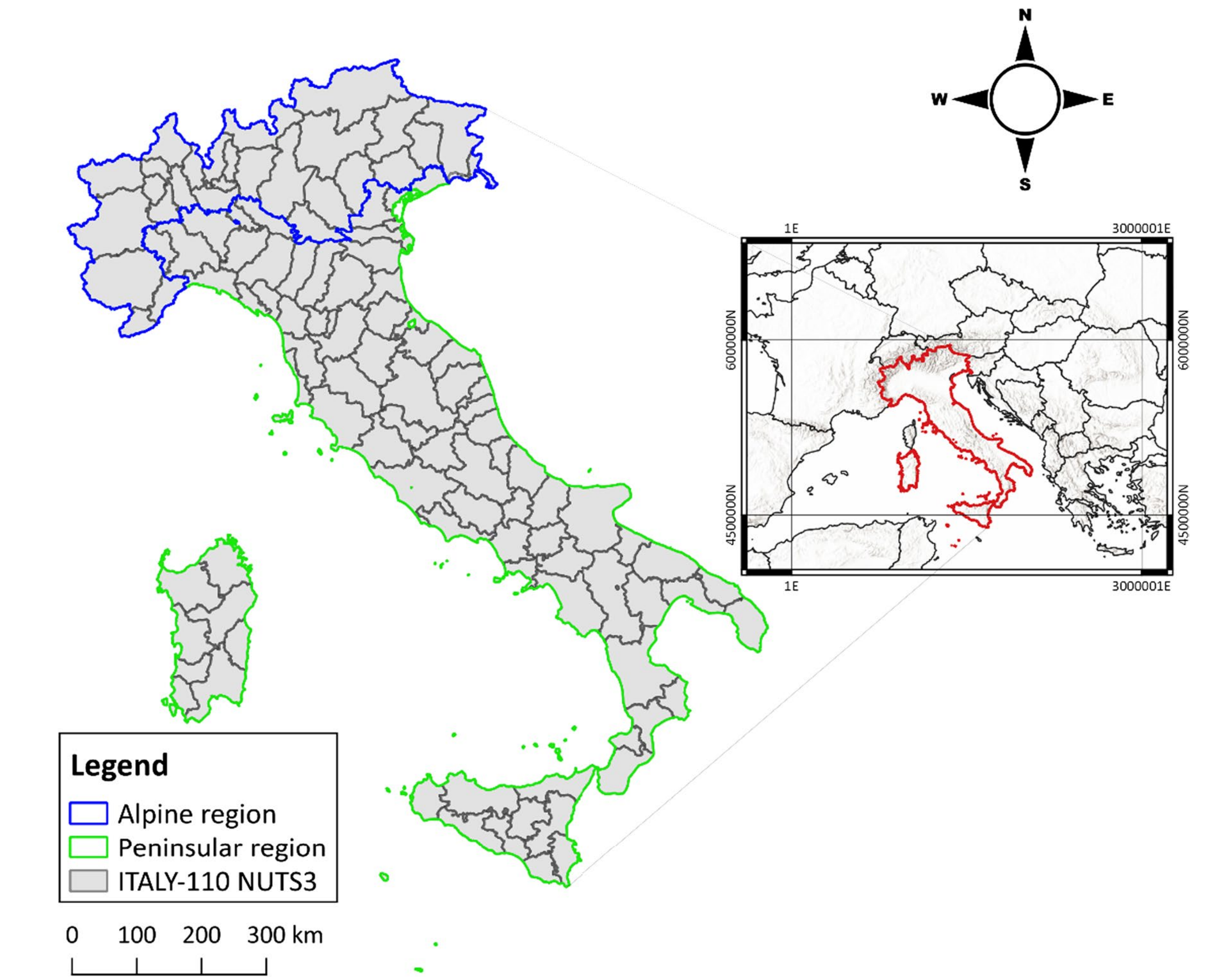

Fig. 2 The 110 Nomenclature of Territorial Units for Statistics, level 3, of the European Union, displayed in the Italian peninsula. The Alpine region and Peninsular region accounted for different climatic and environmental features, where wildfire seasonality metrics were calculated

corrected database available for the entire territory. It consists of 82,064 wildfire events and a total burnt area of about 1 million ha.

To cluster the pyroregions, we extracted wildfire metrics from our data set accounting for density (relative average frequency and burnt area), seasonality (seasonal distribution of events) and stand replacing fire (stand replacing fire ratio). All the metrics were computed at the NUTS3 level (Table 1).

Wildfire density-related metrics were calculated as the ratio between the average number of wildfires (and burnt area) per year and the surface covered by flammable land covers (i.e., CORINE land cover classes 2012) (Table 1). Furthermore, we calculated the mean patch size of burnt area per wildfire event (Fernandes et al. 2016). These wildfire density metrics were considered for their capacity to represent the frequency and incidence of wildfire events in a given landscape (Morgan et al. 2001; Taylor and Skinner 2003; Moreno and Chuvieco 2013; Jiménez-Ruano et al. 2017).

The second group of metrics relates to wildfire seasonality. Indeed, seasonal peaks in fire ignition and burnt areas in Italy change across space, with winter peaks in the Northern Alpine regions and summer peaks in the Southern Mediterranean regions (Valese et al. 2014; Elia et al. 2020a). Analogously to Conedera et al. (2018), who accounted for different climatic and environmental features, we calculated wildfire seasonality metrics by dividing Italy into two separate sub-regions: the Alpine region and the remaining Peninsular region, as shown in Fig. 2. We calculated the number of summer (June to September) wildfire events and burnt area for the Peninsular region and the number of winter (December to March) wildfire events and burnt area for the Alpine region. In addition, for both

Table 1 Wildfire metrics adopted to perform the cluster analysis

Wildfire metrics	Definition	Codes	Description
Fire density	Wildfire/Fuel	W/F	Ratio between the average number of wildfires per year and the land area with available flammable fuel (n $\times$ km^{-2} $\times$ yr^{-1})
	Burnt area/Fuel	BA/F	Ratio between the average burnt area per year and the land area with available flammable fuel (ha $\times$ km^{-2} $\times$ yr^{-1})
	Mean BA/WE	BA/WE	Mean burnt area per wildfire event (ha)
Fire seasonality	Seasonal Wildfires	SeaW	Ratio between the number of wildfires during the main fire season (winter in Northern regions and summer in South Central regions) and the total number of wildfire events
	Seasonal Burnt	SeaB	Ratio between burnt area (ha) during the main fire season (winter in Northern regions and summer in South Central regions) and total burnt area
	Other seasonal wildfires	OSeaW	Ratio between the number of wildfires in seasons others than the main fire season and total number of wildfire events
	Other seasonal burnt	OSeaB	Ratio between burnt area (ha) in seasons other than the main fire season and total burnt area
Stand-replacing fire	Stand-replacing fire ratio	SRF	Incidence of forest cover loss caused by wildfire occurrence

Main fire season = the X months with the highest burnt area (winter in Northern regions and summer in South Central regions); Land area with available flammable fuel = all the codes of the Corine Land Cover 2012 belonging to class 3 (except for 335 and 332) and 243 and 244 (Land principally occupied by agriculture with significant areas of natural vegetation and agro-forestry areas, respectively)

sub-regions we estimated the number of wildfires and burnt area in the remaining months, i.e., other seasons.

The last wildfire metric is an index estimating the capacity of fire to heavily damage vegetation such as Stand Replacing Fire. This kind of event is defined as a fire killing the living overstory trees in a forest generating post-fire forest succession (Halofsky et al. 2018; Stevens et al. 2017). Therefore, to estimate this metric we employed forest cover loss examined by Hansen et al. (2013) to estimate the "stand replacing ratio". The wildfire polygons were overlaid to forest cover losses (2007–2017) and for each fire polygon we calculated the sum of the pixels that were marked as "loss" in 3 years following the fire event. The calculated forest loss area was then used to calculate the "stand replacing ratio" by dividing it by the total fire polygon area.

Climatic and biophysical characteristics

To understand how pyrogeography varies across the Italian peninsula, a set of climatic, biophysical and socio-economic characteristics were selected according to their availability and the potential relation with wildfire occurrence for the period of investigation (Table 2). Data extracted from remote sensing sensors were used to retrieve the climatic and biophysical characteristics. A set of 8-day composite products from the Moderate-Resolution Imaging Spectrometer (MODIS) were collected and further processed using Google Earth Engine (Gorelick et al. 2017). Average maximum and mean land surface temperature (Temp_max and Temp_mean) were derived from MOD11A2 Version (Wan et al. 2015), a multiday composite providing land surface temperature at 1 km of spatial resolution. Mean evapotranspiration (ET_mean) was derived from MOD16A2 (500 m of spatial resolution) (Running et al. 2017), while the mean Normalized Difference Vegetation Index (NDVI_mean) and Normalized Difference Water Index (NDWI_mean) were calculated using the MOD09A1 product (500 m of spatial resolution) (Vermote 2015) as described in Elia et al. (2020b) and Gao (1996). Regarding the validation of the data set, two of the three MODIS products we used (MOD11A2 and MOD09A1) are validated by NASA over a wide temporal and spatial distribution of ground truth measurements and one (MOD16A2) over a smaller number of independents measurements (Wan et al. 2015; Vermote 2015; Running et al. 2017). Following the NASA specification, all the three products are ready for use in scientific publications. All the images were masked from clouds and quality checked using the quality band provided with each MODIS product. ET_mean, NDVI_mean, NDWI_mean and Temp_mean were calculated by averaging the masked images acquired from January 2007 to December 2017 for each NUTS3 region. Temp_max was calculated by averaging the yearly maximum temperature for the same time period.

Droughtness, especially after a period of above average amounts of rainfall stimulating tree and other plant growth, can create conditions of wildfire ignition and spread. A very long drought period can lead to favorable conditions for wildfire occurrence, as all the dried-out vegetation provides abundant fuel to burn (Parente et al. 2016; D'Este et al. 2021). Therefore, for each NUTS3 provinces, we calculated the longest average drought within the period of investigation (2007–2017) using data derived from the SCIA (National System for the collection, processing and dissemination of climate data) website (http://www.scia.isprambiente.it/wwwrootscia/Home_new_eng.html).

Table 2 Summary and description of climatic, socioeconomic and biophysical variables employed in the study

Variables	Codes and units	Description and source
Climatic		
Average max. temperature	Temp_max [°C]	Calculated from MOD11A2 V6, 8-day Land Surface Temperature at 1 km of spatial resolution. Temp_mean is the average from 2007 to 2017 and Temp_max is the average maximum yearly temperature within this period
Average mean temperature	Temp_mean [°C]	
Evapotranspiration	ET_mean [kg/m^2]	Average for 2007–2017, calculated from MOD16A2 V6, 8-day Evapotranspiration composite at 500 m of spatial resolution
Longest drought period	Longest_drought_period [days]	The average longest drought within the period of investigation (2007–2017)
Biophysical		
NDVI mean	NDVI_mean	Average for 2007–2017 calculated from MOD09A1 V6, 8-day Surface Spectral Reflectance composite at 500 m of spatial resolution
NDWI mean	NDWI_mean	
Elevation	elev.mean [m asl]	Zonal mean derived from NASA SRTM DEM at 90 m of spatial resolution, v4.1 (Jarvis et al. 2008)
Slope	slope.deg [degrees]	
Latitude	Latitude][decimal degrees]	Latitudinal location of the centroid for each NUTS3 province
Density of rivers	river.density [km/ha]	Derived from the CCM2 River and Catchment Database for Europe V 2.1. River density was calculated only considering the main rivers
Mean distance to coast	coast.dist.mean [km]	
Artificial surfaces	Artif.surf [%]	Percentage occupied by artificial surfaces (Level 1) according to Corine Land Cover 2012 (CLC 2012)
Arable lands	Arable.land [%]	Percentage occupied by arable lands, permanent crops, pastures and heterogeneous agricultural areas (Level 2) according to CLC 2012
Permanent crops	Perm.crop [%]	
Pastures	Pastures [%]	
Heterogeneous agricultural areas	Agric.areas [%]	
Broad leaved forests	Broad.leaved.for [%]	Percentage occupied by broad-leaved, conifer and mixed forests (Level 3) according to CLC 2012
Conifer forests	Conif.for [%]	
Mixed forest	Mixed.for [%]	
Shrub/herbaceous vegetation association	Shr.herb.veg [%]	Percentage occupied by scrub/herbaceous vegetation associations and areas with little or no vegetation (Level 2) according to CLC 2012
Little or no vegetation	little.no.veg [%]	
Socioeconomic		
Population density	pop.dens [inhab/km^2]	Eurostat [demo_r_d3dens] data from 2012
Level of employment	Perc.employed [%]	Eurostat [nama_10r_3empers] data from 2012
Gross Domestic Product	GDP [1000 EUR/km^2]	Eurostat [nama_10r_3gdp] data from 2012
Density of tourist establishments	dens.tour.establ [#/km^2]	Includes hotels; holiday and other short-stay accommodations; camping grounds, recreational vehicle parks and trailer parks. Eurostat [tour_cap_nuts3] data from 2011
People with basic education	Perc.people.basic.educ [%]	Percentage of people with basic educational level (0–2). Istat [DICA_GRADOISTR1] data from 2011

NDVI Normalized Difference Vegetation Index, *NDWI* Normalized Difference Water Index

Other biophysical variables were retrieved from geospatial data sets. The mean elevation and mean slope degree were derived from the NASA Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) at 90 m of spatial resolution (v4.1) (Jarvis et al. 2008). Latitude (Latitude) was derived from an ArcMap 10.5 calculation using the centroid of each NUTS3 polygon. The density of rivers and mean distance to coast were calculated using the CCM2 River and Catchment Database for Europe V 2.1. Data regarding the type of land cover, vegetation characteristics and fuel availability were obtained from CORINE Land Cover 2012, calculated as the percentage occupied by different classes within each NUTS3 province. Our rationale for using 2012 data was that they more suitably represented the scenario of wildfire metrics for 2007–2017, than the 2006 and 2018 versions.

Socioeconomic characteristics

Historical fire statistics in Italy suggest that wildfires have a positive relationship with the human sphere, since negligence and arsons represent the major causes of wildfires

(Elia et al. 2019). Lack of caution and care in forestry or agricultural practices (e.g., burning of stubble) can lead to fire ignition and often to extreme wildfire events (Guo 2021). Therefore, it is crucial to include the human system when exploring pyrogeography in Italy as well as the differences between North and South or between densely populated and remote areas.

In light of the above, and according to previous studies (Lein and Stump 2009; D'Este et al. 2020; Giannico et al. 2021), socioeconomic characteristics include population density, level of employment, Gross Domestic Product (GDP), density of tourist establishments and the percentage of people with basic education. These data were extracted from the Eurostat Database of the European Union and calculated at the NUTS3 level. We used data from 2012 or the closest date available. Table 2 reports all the climatic, socioeconomic and biophysical explanatory variables adopted in the study.

Cluster and statistical analyses

Cluster analysis is a technique employed to partition a set of objects according to perceived similarities. It is a formal study of algorithms and methods for grouping or classifying such objects. To obtain a consistent partitioning process the following must be considered: (1) objects extracted and used from the original database may be the most representative features; and (2) the selected algorithm must be designed according to the characteristics of the problem.

In the wide panorama of cluster analyses (see Xu and Tian 2015 for a more comprehensive review), we opted to use the Affinity Propagation (AP) algorithm, developed by Frey and Dueck (2007). AP is based on the core idea that all data points (e.g., objects) can be candidate centers of potential clusters and that negative Euclidean distance is used to measure the affinity between pairs of data points. Therefore, as the sum of the affinity between pairs of data points increases, the probability that this data point is the cluster center increases. AP has numerous advantages over related cluster analyses. The first and most important advantage is that the number of clusters does not need to be preset and, second, the algorithm is insensitive to outliers. Furthermore, AP is suitable for small- and medium-sized data sets, hence, it fits well with our data set which includes 110 NUTS3 provinces (Lu and Carreira-Perpinan 2008; Xu and Tian 2015). The analysis was performed using the "APCluster" package for R developed by Bodenhofer et al. (2011).

To test the significance of differences between clusters according to their climate, socioeconomic and biophysical characteristics, we used a one-way analysis of variance (ANOVA) followed by a Tukey's Post-Hoc Test.

Lastly, to test for relationships between the climatic, biophysical, and socioeconomic characteristics and the uncovered pyroregions we performed a distance based Redundancy Analysis (RDA). The nature of this calculation is very sensitive to collinearity among the variables, especially when data sets have many variables as in our case. In these circumstances, we tried to minimize collinearities by not including highly correlated explanatory variables (Additional file 1: Figure S1).

RDA is a non-symmetric canonical correlation analysis that explores the relationship between two tables of variables, Y and X. In our case, we considered wildfire metrics as the response variable (e.g., Y) and the climatic, biophysical, and socioeconomic characteristics as the explanatory variable (e.g., X).

At aims to carry on the RDA we needed to decide the distance measure to use. One way to do this is by looking at the rank correlations between dissimilarity indices and gradient seperation: the higher the value the better. On the base of the 'rankindex' function of the "vegan" package for R (Dixon 2003) we found Euclidean to be the best distance measure to use. Furthermore, we provided as supplementary material (Additional file 1: Figure S2) a stepwise selection to understand more in depth what are the main drivers affecting spatial configuration of pyroregions.

The entire data set was scaled to unit variance and the analysis was carried out using the same abovementioned package for R. The significance of the model, variables, and RDA axes were checked using an ANOVA-like permutation test with 999 iterations ($\alpha = 0.001$).

Results

Current pyroregions in Italy

The AP analysis identified seven different pyroregion clusters across Italy (Fig. 3). According to the high environmental heterogeneity of the Italian peninsula, we named the seven clusters as follows: Large summer wildfires (LAS) (14—NUTS3 provinces); Extreme stand-replacing summer wildfire (EXS) (24); Medium density summer wildfires (MDS) (28); Subalpine low density wildfires (PLD) (16); Alpine high density wildfires (AHD) (14); Alpine High Stand-replacing wildfires (AHS) (7); and Reduced stand-replacing wildfires (RES) (7).

LAS was the first cluster identified by the analysis with 14 NUTS3 provinces. It covers two important areas of Italy: the first is the central part of the peninsula, where the highest mountain in the Apennines is found, named Gran Sasso (Fig. 3), and includes the Parco Nazionale del Gran Sasso and Monti della Laga; the second is the northern side of two principal Italian islands. This cluster exhibited the highest values of mean burnt area per wildfire event (BA/WE = 15.493), seasonal burnt area

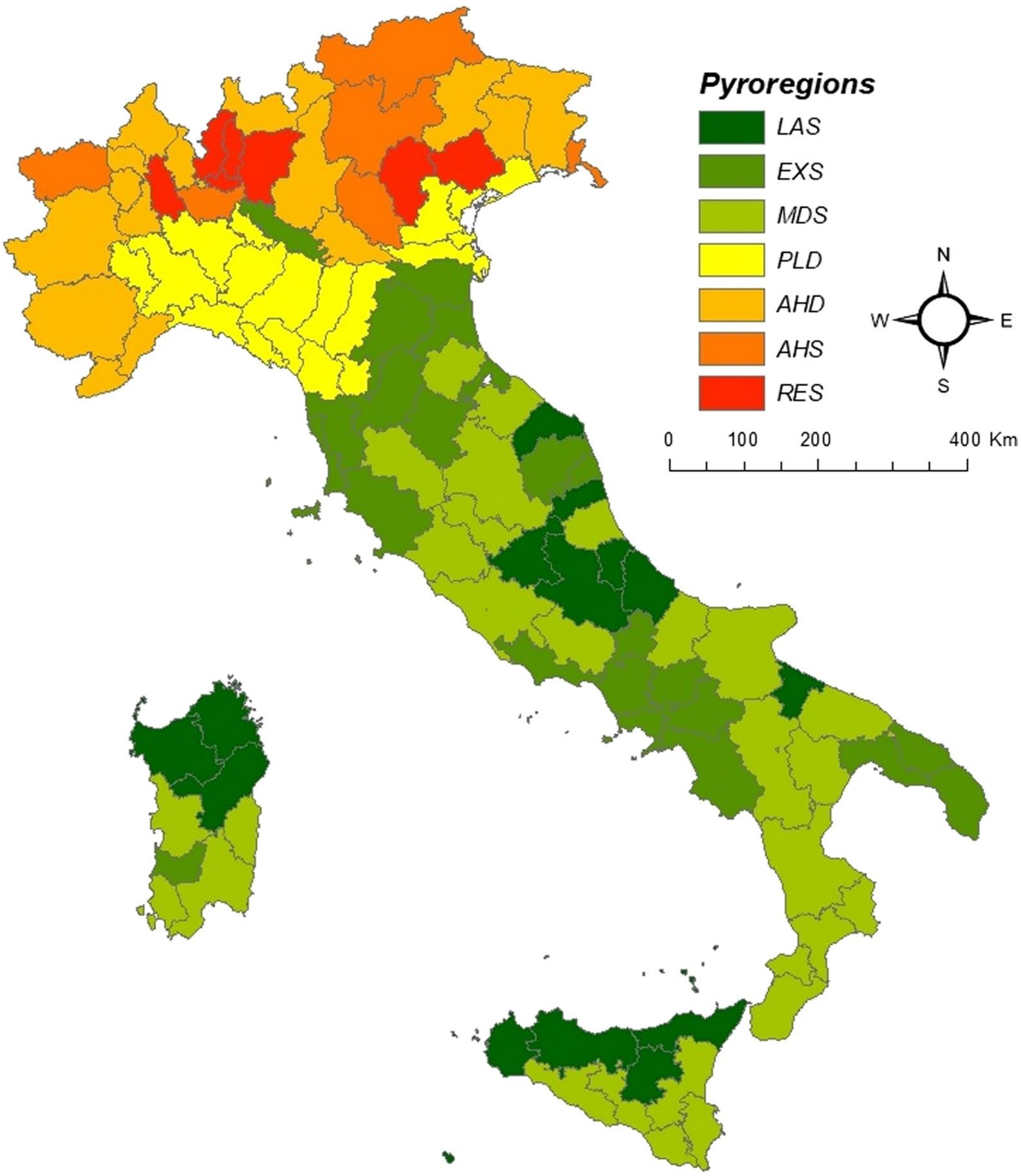

Fig. 3 Seven pyroregions uncovered by the Affinity Propagation analysis across the entire study area: Large summer wildfires (LAS) (14—NUTS3 provinces); Extreme stand-replacing summer wildfire (EXS) (24); Medium density summer wildfires (MDS) (28); Subalpine low density wildfires (PLD) (16); Alpine high density wildfires (AHD) (14); Alpine High Stand-replacing wildfires (AHS) (7); and Reduced stand-replacing wildfires (RES) (7)

(SeaB = 0.950), stand replacing fire ratio (SRF = 0.017) and burnt area/fuel ratio (BA/F = 1.55E-02) during the period under study (Table 3). However, LAS showed the lowest values of OseaB (0.050) suggesting that wildfires rarely occur in other seasons of the year.

EXS and MDS are the two largest pyroregions including 24 and 28 NUTS3 provinces, respectively. The EXS pyroregion is represented by 13 NUTS3 belonging to the central part of the peninsula, while the remaining 11 belong to the southern area and include relevant biodiversity hotspots, such as the Salento peninsula and Cilento Mounts. The EXS pyroregion is the cluster with the highest ratio between the average number of wildfires per year and the available flammable fuel (W/F = 5.45E-03). It exhibited the highest value of SRF (0.020) and is characterized by high values of seasonal occurrence of fires and burnt area (SeaW and SeaB of 0.828 and 0.914, respectively) (see Table 3). The MDS pyroregion includes important wildfire hot spots across the peninsula, such as the Gargano promontory, the

Table 3 Average values of the wildfire metrics used to perform the Affinity Propagation analysis grouped per cluster (see Table 1 for all codes and Fig. 3 for pyroregion acronyms)

Pyroregions	W/F	B/F	BA/WE	SeaW	SeaB	OSeaW	OSeaB	SRF
LAS	1.57E-03	1.55E-02	15.493	0.837	0.950	0.163	0.050	0.017
EXS	5.45E-03	9.73E-03	2.013	0.828	0.914	0.172	0.086	0.020
MDS	1.72E-03	8.35E-03	5.084	0.871	0.943	0.129	0.057	0.012
PLD	3.37E-04	4.41E-04	1.529	0.496	0.515	0.504	0.485	0.013
AHD	2.26E-04	1.15E-03	5.692	0.617	0.522	0.383	0.478	0.010
AHS	4.13E-04	3.22E-04	0.808	0.279	0.413	0.721	0.587	0.015
RES	4.85E-04	7.28E-04	1.491	0.824	0.841	0.176	0.159	0.003

Sila mountain plateau located in Calabria, and South-eastern Sicily almost covered by the Etna volcano. MDS is characterized by medium values of fire density and high seasonality. For example, MDS displayed a BA/WE value of 5.084 ha, the highest SeaW value (0.871) and the second highest SeaB value (0.943).

The PLD cluster includes 16 NUTS3 provinces in the north-central part of the peninsula. It covers the principal flatland of Italy, named Pianura Padana. The PLD exhibited a low value of fire density metrics (W/F = 3.37E-04; BA/F = 4.41E-04), since the landscape consists mostly of agricultural lands, where few wildfires occur due to lack of flammable fuels prone to fire disturbance (Elia et al. 2020b).

Lastly, AHD, AHS, and RES represent the Alpine pyroregions in our study and include 14, 7 and 7 NUTS3 provinces, respectively (Fig. 3). Although they represent one third of the potential flammable fuel in Italy, these Alpine pyroregions showed low values of wildfire density, especially the W/F and BA/F values (Table 3). For example, RES showed the lowest W/F value equivalent to 4.85E-04. Among the Alpine pyroregions, AHD is the largest cluster displaying the second highest fire size BA/WE = 5.692 ha. This pyroregion covers most of NUTS3 from west to east including many national parks, such as Val Grande, Gran Paradiso, Stelvio, Dolomiti Bellunesi, and natural ecosystems such as the Garda and Iseo lakes.

We considered AHS as a group of outliers compared to the other alpine pyroregion, since the values demonstrate an opposite pattern in terms of fire density, seasonality and stand replacing fire ratio. This cluster exhibited the lowest fire size BA/WE = 0.808 ha, even if fires occur with a high SRF (0.015). Although it is an Alpine pyroregion, it presents a seasonality that is extremely different from the other two pyroregions. In fact, the values expressed a higher number of other seasonal wildfires (OSeaW = 0.721) than of seasonal wildfires (SeaW = 0.279) in the main fire season (i.e., winter) (Table 3).

Comparison among pyroregions

The one-way ANOVA, followed by the Tukey's Post-Hoc Test, allowed to highlight the main differences of the uncovered pyroregions from the biophysical, socioeconomic and climatic point of view. The differences among pyroregions were significant (ANOVA $P < 0.05$) for all of the variables with the exception of Arable. land, Shr.herb.veg, Broad.leaved.for, NDVI_mean, dens. tour.establ.N.km^2 and ET_mean, where no significant differences were found. The distribution of values for each biophysical, socioeconomic and climatic variable is shown in Fig. 4. Post-hoc Tukey's honestly significant differences ($P < 0.05$) among pyroregions are represented by different letters above each box, based on the test results from the R package multcompView (Graves et al. 2015).

In general, the most significant differences were found in latitude, mean and maximum temperature, percentage of people with basic education and mean distance to coast with 13, 13, 13, 12 and 11 significant differences among clusters, respectively (Fig. 4). The largest differences were found between the following pairs of clusters: MDS and AHD (14 times), MDS and AHS (13 times), EXS and AHD (12 times), EXS and AHS (12 times), and LAS and AHS (11 times). On the contrary, for the abovementioned variables no significant differences were found between AHD and AHS, EXS and LAS, and MDS and LAS.

In terms of biophysical factors, the majority of significant differences were found for the variables mean distance to coast, presence of conifer forests and mean elevation (Fig. 4). The MDS, LAS, PLD and EXS pyroregions were found to be grouped for all variables with the exception of river density, where PLD was significantly different from the MDS pyroregion. Similarly, the AHS, RES and AHD pyroregions were always grouped together except for the artificial surfaces and conifer forest, where RES was significantly different from AHD and AHS, respectively.

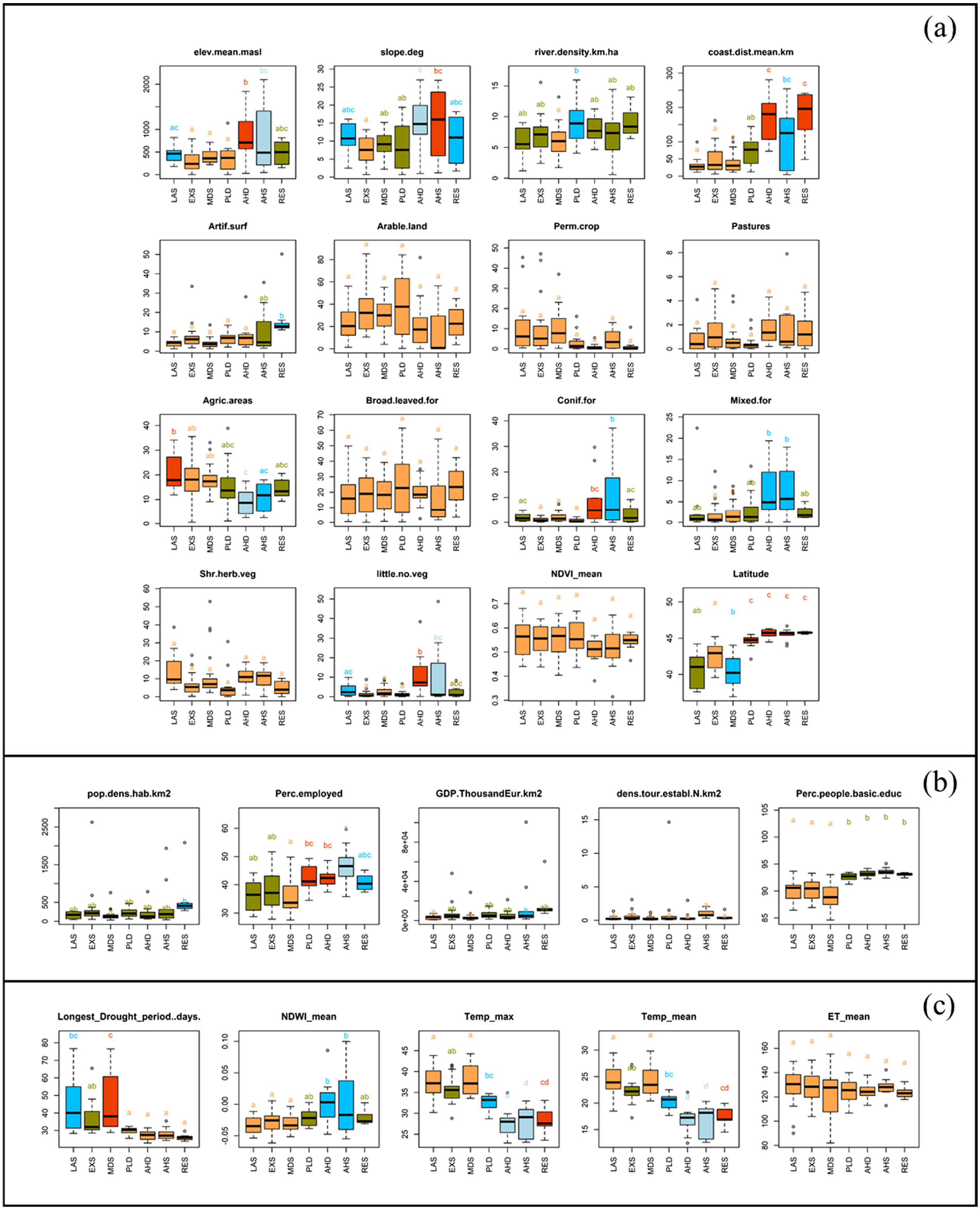

Fig. 4 Box plots showing the distribution of values for each biophysical (**a**), socioeconomic (**b**) and climatic (**c**) variable. For each plot, a pyroregion was assigned to a specific group represented by a letter above each box, in accordance to Post-hoc Tukey honestly significance difference. Clusters belonging to the same group were not significantly different ($P < 0.05$)

According to the Post-hoc Tukey's test, in the spectrum of socioeconomic factors, no differences between clusters were found for the variable density of tourist establishments. Significant differences were found between pyroregions in all the other variables. A significant difference was found in population density between both the MDS and RES pyroregions. A similar pattern was found for the variable Gross Domestic Product (GDP), where the AHS cluster had significantly higher values than both the MDS and LAS clusters. In terms of the percentage of people with basic education, a significant difference was found between the group formed by the MDS, LAS and EXS pyroregions and the group formed by AHS, RES, AHD and PLD pyroregions. In regards of the level of employment, no significant differences were found among the MDS, LAS and EXS pyroregions, all of which had lower values in comparison with the AHS, RES, AHD and PLD pyroregions; the latter, overall, presented higher values for both aforementioned socioeconomic factors.

A great number of significant differences among clusters were found in the climatic sphere, except for the variable mean evapotranspiration (ET_mean), where no differences were found. Considering Temp_max and Temp_mean, the MDS, LAS and EXS pyroregions, having higher temperatures, were grouped together and found to be significantly different from the AHS, RES and AHD pyroregions registering lower maximum and mean temperatures. For both temperature variables the PLD pyroregion was in the middle, presenting differences with the MDS and LAS as well as the AHS, RES and AHD pyroregions. Drought periods were substantially higher for MDS and LAS, except for EXS, presenting significant differences with all of the other pyroregions, although the variance was very high for both clusters. The differences in NDWI were only found between the group composed by AHS and AHD and the group composed by MDS, LAS and EXS.

Statistical analysis performance

We tested the Pearson's correlation coefficient to estimate collinearities among the explanatory variables. The higher the value of the Pearson coefficient, the higher the correlation. We identified the maximum and minimum variable correlation threshold as 0.80 and − 0.80, respectively. If the variable was above or below these values, it was omitted from subsequent analysis (Elia et al. 2020a, b).

The RDA in Fig. 5 shows the relationships between wildfire metrics and all the biophysical, socioeconomic and climatic characteristics of NUTS3 provinces in

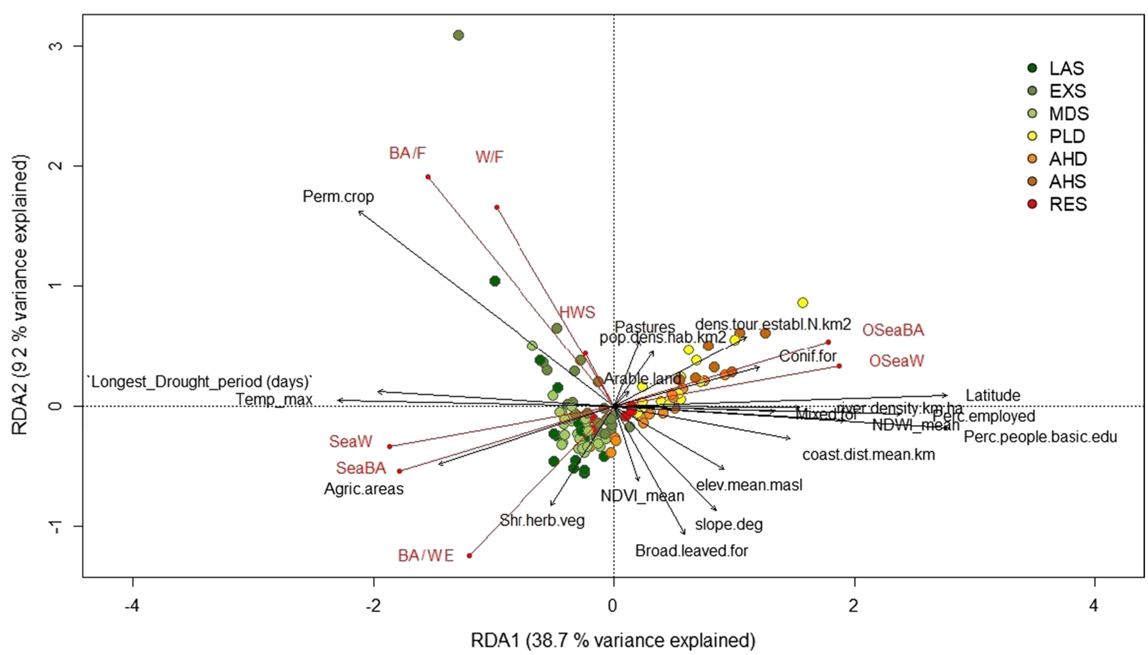

Fig. 5 Biplot relationships between wildfire metrics (red text) and biophysical, socioeconomic and climatic variables (black text) of NUTS3 provinces in Italy. Each dot represents a NUTS3 province, and the colors denote belonging to a pyroregion: Large summer wildfires (LAS); Extreme stand-replacing summer wildfire (EXS); Medium density summer wildfires (MDS); Subalpine low density wildfires (PLD); Alpine high density wildfires (AHD); Alpine High Stand-replacing wildfires (AHS); and Reduced stand-replacing wildfires (RES). The arrow length and direction represent the variance that can be explained by the variables. The direction of an arrow suggests an increasing magnitude of the variable, while the perpendicular distance between orders and variable axes in the biplot represent their correlations (All variables are reported in Table 2.)

Italy. Each dot represents a NUTS3 province, while the colors denote belonging to a pyroregion. The arrow length and direction represent the variance that can be explained by the variables. In addition, the direction of an arrow suggests an increasing magnitude of the variable, while the perpendicular distance between wildfire metrics and axes in the biplot is inversely related to their correlation with the axes (Fig. 5).

The model displayed an adjusted R^2 of 0.43. The first four RDA axes were significant ($P<0.001$) and explained 40.1%, 9.7%, 3.5% and 2.1% of the model variance, respectively. The variables that highly correlated to RDA1 were temperature and drought, which are inverse to the axes scores, and distance from the coast and level of employment, which correlated positively to the axes. As regards fire metrics, fire density and burnt area in the main fire season correlated negatively, while the reciprocals in other seasons were positively correlated. The variables that positively correlated to RDA2 were mainly population density and related proxies (e.g., dens.tour.establ), and permanent crops, while slope, elevation and natural vegetation types (e.g., Broad.leaved.for, shrublands) were negatively correlated. Fire density, burnt area, and stand replacing fire ratio correlated positively, while fire size correlated negatively. RDA1 represents a gradient of fire proneness from left to right which is collinear with a North–South gradient, as reflected by the distance from the coast and level of employment (Oliveira et al. 2012; Fox et al. 2018). RDA2 reflects a gradient of increasing anthropization from the lower to upper quadrants, from more natural and remote areas at higher elevation to densely populated areas.

The RDA suggested a clear distinction between the pyroregions. The Alpine pyroregions (AHD and RES) and PLD are displayed in the North–East quadrant and are collinear with the socioeconomic variables (e.g., pop.dens and dens.tour.establ) and biophysical drivers (e.g., Conif. for, Arable.land, and Pastures).

On the contrary, the RDA biplot suggested that the wildfire metrics of the peninsular pyroregions (LAS, EXS, MDS) are positively correlated almost with climatic variables, such as temperature, and drought period and three biophysical variables, such as agricultural areas, presence of shrubland, herbaceous vegetation and permanent crops. The peninsular pyroregions (LAS, EXS and MDS) were mostly grouped in the South–West quadrant, suggesting an opposite pattern compared to the Alpine pyroregions. The AHS pyroregion showed a more heterogeneous pattern in terms of variables potentially affecting wildfire metrics. Its dots, in fact, are almost located, where the two axes meet suggesting that in this pyroregion wildfire metrics have contrasting correlations, since it is positively related to both fire seasonality and fire density.

Discussion

In this study, we highlight and classify pyrosimilarities by uncovering current pyroregions using the Italian territory as a test bed. Italy displays an outstanding variety of landscapes and landforms due to its complex geological history, climate regimes and human impacts; this heterogeneity, in turn, reflects on the pyrogeography of the territory. From a geographical point of view, we can distinguish the Alpine region, which displays abrupt climatic and environmental changes from the rest of the peninsula, as well as a peculiar anthropic influence on its landscapes (Conedera et al. 2017). The rest of the Italian peninsula is heavily influenced by the Mediterranean Sea, as well as by the presence of mountain chains and plains. In such a context, we uncovered seven current pyroregions on the basis of wildfire metrics related to density, seasonality and stand replacing fire ratio.

The RDA analysis identified two main gradients partly explaining the variability of wildfire metrics observed in the uncovered pyroregions: (1) a fire-climatic gradient (i.e., RDA1), characterized by increasing temperatures and exposure to droughts, which coincides with a geographical gradient from North to South, as indicated by distance from the coast, and (2) an anthropic pressure gradient (i.e., RDA2) displaying increasing population density in areas at a lower elevation. As expected, these drivers had a major influence on fire density and burnt area over available fuels and stand replacing, which were associated to warm-dry climate and high anthropic pressure. Our findings confirm the key role of human presence (e.g., population density) in shaping pyrography in Italy (Lafortezza et al. 2015; Ferrara et al. 2019; Ascoli et al. 2021). Similar results have emerged in other southern European regions. Curt et al. (2016) found that the 88% of fires in Southern France is imputed to human settlements and infrastructures. Rodrigues et al. (2019) identified four different cluster zones determined by drivers of large-fire in Spain. They found a high variability from zone to zone in terms of fire influence, although in some locations the proximity to human settlements and agricultural practices were relevant.

Notably, a metric such as mean size of single fire events was larger, where human pressure was lower, i.e., in remote mountain regions, where elevation and slope increase, fire control is less effective and continuous fuels are expected. Contrarily, peri-urban fringes represent hot spots for smaller and frequent wildfires (Elia et al. 2014; Lafortezza et al. 2015; Carlucci et al. 2019). Interestingly, our analysis showed a clear distinction between regions, where wildfire disturbance is concentrated in a single major season, strongly correlated to high temperatures and drought (peninsular region), and regions, where wildfires are distributed over the course of several seasons (most of Alpine region).

For instance, the LAS, MDS and EXS pyroregions in South Central Italy displayed the highest fire density and burnt area in a single fire season (i.e., summer). The pyrogeographic analysis correctly classified those provinces which, though located in the North (e.g., Cremona), experienced a summer fire season in the period of investigation (2007–2017) and, therefore, belong to one of the South Central clusters (i.e., EXS). These pyroregions are characterized by large and stand replacing wildfires, displaying the highest value of mean burnt area per wildfire event (e.g., LAS = 15.493 ha), and are among the regions with the majority of post-fire forest cover losses (Table 3). This is the result of a flammable landscape, mostly characterized by Mediterranean sclerophyllous and pine vegetation which encourages crown fire behavior (Nunes et al. 2005; Sebastián-López et al. 2008), high temperatures and long periods of drought in summer (Frate et al. 2018; Elia et al. 2019; D'Este et al. 2020), as highlighted by Tukey's Post-Hoc Test. Consequently, these regions, and particularly LAS, are prone to extreme fire growth in summer (Morresi et al. 2019; Di Ludovico and Di Lodovico 2020; Salis et al. 2021). However, during the rest of the year, the climate in these regions is milder and wetter making the vegetation less flammable, although some minor fires do occur.

The Alpine pyroregions (i.e., AHD, AHS and RES), on the other hand, showed lower values for fire density and burnt area over available fuels compared to the Mediterranean pyroregions. In these clusters, diverse social and biophysical factors determine a particular pyrogeography. The reduced usage of fires in agro-pastoral systems, less frequent fire-prone weather, and high control of social activity partly contribute to lower wildfire ignitions (Bebi et al. 2017; Vacchiano et al. 2018). Furthermore, relatively less fire-prone vegetation and fire-conducive climate make wildfires grow generally slower in most parts of these regions, which increases fire control capacity with cascading effects on burnt area and fire size. However, large wildfires sporadically occur, particularly in AHD, when snow-free dry winters coincide with warm-dry winds (foehn), spreading fire on steep slopes and inner remote valleys, where fire-fighting is no longer feasible (Reinhard et al. 2005; De Angelis et al. 2012; Valese et al. 2014; Mofidi et al. 2015). In contrast to Mediterranean pyroregions, the Alpine clusters denoted a more balanced wildfire occurrence and burnt areas between the main fire season in winter and other seasons (see Table 3), particularly in early spring and late summer. This finding reflects the interaction between biophysical and socioeconomic factors (Lafortezza and Giannico 2019; Spano et al. 2020a). Indeed, in these regions fire-prone vegetation and fire-conducive climate might align in several seasons throughout the year. For instance, in winter grasses are fully cured, broad-leaved litter accumulates, and prolonged dry-windy periods last until early spring, and in late summer occasional long droughts and heat waves dry out vegetation before the fall, these regions appears similar to Mediterranean areas, as occurred in 2003 and 2017 (Ascoli et al. 2013; Valese et al. 2014). The socioeconomic sphere also plays a relevant role in distributing wildfires throughout the year. For example, wildfire ignition using silvopastoral practices may take place both in late winter and early spring to renew pastures (Tinner et al. 2005; Ascoli and Bovio 2010; Rey et al. 2013; Schwörer et al. 2014; Chergui et al. 2018) and in late summer and early fall to manage chestnut forests (Ascoli and Bovio 2010; Gullino et al. 2020). Tourist activities in summer may also contribute to wildfire ignition in this season (Arndt et al. 2013).

Level of education showed a similar correlation to the other human variables. Many authors (Kellens et al. 2013; Oliveira et al. 2020a, b) have well documented how natural and man-made disasters are related to educational level. Being well informed, people with high levels of education show more awareness of and sensitivity towards natural risks (i.e., wildfires), confirming higher caution and care when dealing with them (e.g., renewal of pastures, burning of stubble, releasing flammable waste) (Crociata et al. 2016; Dell'Olio et al. 2017; Spano et al. 2020b). However, the cultural aspect of wildfires in Italy deserves a more in-depth discussion, since we believe that the wildfire issue is non-strictly linked to education or poverty, but to a more comprehensive North–South socioeconomic gradient reflected in wildfire metrics (Schneider 2020). Several aspects must be considered when debating the wildfire–education interaction. Michetti and Pinar (2019) highlighted that, although higher levels of education lead to decreases in the number of fire events and total area burnt, southern Italy represents an exception. For example, the use of fires, or the simple acceptance of them (e.g., prescribed fires), is quite different between North and South.

Prescribed fires are perceived differently going from South to North. In Southern Italy, despite the prevention phase must be strongly improved, silvicultural interventions of prescribed fires are more endorsed (e.g., Campania region) than in the northern Italy (i.e., Bozen province), where this practice is considered harmful for forest resources (Ascoli and Bovio 2010). The recreational use of fires (e.g., campfires, fireworks) is allowed with diverse rules according to the provinces, and even where rules are similar the response of people changes from North to South (Kovacs et al. 2017). For instance, in the North Italy (e.g., Veneto region) campfires are considered an element of high wildfire risk compared to southern Italy, where many public and religious events use fireworks as a main tourist attraction. The abovementioned socioeconomic gradient is mostly reflected in the fire suppression system. From North to South, the systems of wildfire suppression differ in terms of organization, resources and control of the territory. The regions of Tuscany and Piedmont have more efficient and cost-effective wildfire suppression systems compared to most southern regions (Fasolo 2018).

Limitations

Even if our study can seem characterized by a regional focus, we strongly find merit in our work. It should be stressed that Italy is the third most fire affected country of Europe (San-Miguel-Ayanz et al. 2020). Addressing these kinds of studies is important for several reasons such as deaths, global CO_2 emissions, forest and biodiversity loss, huge costs of firefighting and governmental money contributions to help citizens. We also think that examples of pyrogeography systematization are not common in Europe yet, but they are needed to raise the fire management to a broader level of analysis. In addition, the adopted clustering method has novelties in the context of wildfires and the entire statistical approach resulted rather straightforward and solid. However, there are some relevant limitations that need to be assessed.

First, we are aware that our study has limitations in terms of the time span of the analysis, given the relatively short period of consistent wildfire data available (2007–2017). Currently, there are several sources to extract fire data sets longer than the one adopted in this study, such as "globalfiredata.org" or EFFIS (European Forest Fire Information System, https://effis.jrc.ec.europa.eu/). However, the number of fires and the amount of burnt area omitted by these sources is remarkable. For instance, while our data set accounted for 82,064 fire events during the period of investigation (2007–2017), the abovementioned sources recorded 2615 fire events. For this reason, we opted to use a more detailed data sets even if relatively short.

Second, we believe that the study would benefit from adding a metric related to wildfire severity. Nevertheless, Italy currently lacks a national database of wildfire severity, except for small areas that are analyzed by local and event-specific studies.

The last limitation concerns the stand replacing fire ratio derived by forest cover loss. This metric is based on the fundamental assumption that the cover loss within the wildfire perimeters was due exclusively to direct and indirect consequences of fire occurrence.

Conclusion

This study proposes a systematic pyrogeographic analytical approach of the Italian peninsula presenting a method for uncovering current pyroregions on the basis of their pyrosimilarities across the Italian territory at large.

Based on adopted wildfire metrics, the pyroregions uncovered by this approach can be implemented in fire management plans and civil protection strategies. Furthermore, understanding how pyrogeography varies according to biophysical, socioeconomic and climatic drivers can improve the prediction of alterations associated with future fire regimes, especially in a context of climate change and intense human intervention on landscapes (Bowman et al. 2020).

Currently, many authors hastily identify wildfire occurrence as linked to education, employment, or population density. In this work we highlighted the importance of the North–South gradient, which represents one of the most important drivers of pyrogeography resulting from the variations in both climatic and socioeconomic conditions, which are difficult to disentangle. Based on these findings, decision makers could design efficient interventions to mitigate wildfire occurrence by acting not only on biophysical drivers (e.g., forest fuels) but also on developing new policies aimed at rebalancing the socioeconomic differences between pyroregions.

In addition to the important study results found for Italy, our fully replicable analytical approach can be applied at multiple scales and used for the entire European continent to uncover new and larger pyroregions. This could create a basis for the European Commission to promote innovative and collaborative funding programs (e.g., H2020, Life, Interreg projects) between regions that demonstrate pyrosimilarities.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13717-022-00360-6.

Additional file 1. Supplementary material.

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Authors' contributions
ME: conceptualization, methodology, formal analysis, investigation, writing and revising. VG: formal analysis, writing, and revising. DA and JA: data collection, writing and revising. GS (Giuseppina Spano) and MD: revising. RL: supervising and revising. GS (Giovanni Sanesi): supervising, revising, and funding acquisition. All authors read and approved the final manuscript.

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The data sets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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Not applicable.

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Competing interests
The authors declare that they have no competing interests.

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