Int J Appl Earth Obs Geoinformation 74 (2019) 314–321

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Remotely-sensed phenology of Italian forests: Going beyond the species

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ARTICLE INFO

Keywords:
Discriminant analysis
MODIS EVI
Pheno-clusters
Time-series
Vegetation phenology

ABSTRACT

Remotely sensed observations of seasonal greenness dynamics represent a valuable tool for studying vegetation phenology at regional and ecosystem-level scales. We investigated the seasonal variability of forests in Italy, examining the different mechanisms of phenological response to biophysical drivers. For each point of the Italian National Forests Inventory, we processed a multitemporal profile of the MODIS Enhanced Vegetation Index. Then we applied a multivariate approach for the purpose of (i) classifying the Italian forests into phenological clusters (i.e. pheno-clusters), (ii) identifying the main phenological characteristics and the forest compositions of each pheno-cluster and (iii) exploring the role of climate and physiographic variables in the phenological timing of each cluster. Results identified four pheno-clusters, following a clear elevation gradient and a distinct separation along the Mediterranean-to-temperate climatic transition of Italy. The "High-elevation coniferous" and the "High elevation deciduous" resulted mainly affected by elevation, with the former characterized by low annual productivity and the latter by high seasonality. To the contrary, the "Low elevation deciduous" showed to be mostly associated to moderate climate conditions and a prolonged growing season. Finally, summer drought was the main driving variable for the "Mediterranean evergreen", characterized by low seasonality. The discrimination of vegetation phenology types can provide valuable information useful as a baseline framework for further studies on forests ecosystem and for management strategies.

1. Introduction

Monitoring vegetation phenology helps to detect the changes in ecosystem functions, providing baseline data to track vegetation dynamics related to events such as drought, fire, spring frost, land use changes, climate oscillations, etc. (Peñuelas et al., 2004; Xiao et al., 2015; Bascietto et al., 2018; Workie and Debella, 2018). The recent establishment of the USA National Phenology Network (USA-NPN; https://www.usanpn.org/), the Pan European Phenology Project (PEP725; http://www.pep725.eu/), the GLOBE phenology project (https://www.globe.gov/web/phenology-and-climate), suggest the need for a greater understanding of biological responses to a changing environment at different geographical scales (Lim et al., 2018). Remote sensing observations of seasonal greenness dynamics take advantage of the potentialities of high temporal resolution satellites (like MODIS) and represent a valuable tool for studying vegetation phenology at scales consistent with ecosystem-level processes and regional climate information (White and Nemani, 2006; Polgar Caroline and Primack Richard, 2011; D'Odorico et al., 2015; Xu et al., 2017).

Remotely-sensed phenology is the study of the timing of vegetation seasonal pattern of growth, senescence and dormancy, in a spatially aggregated form (e.g. pixel size of metres to km) (Gonsamo et al., 2012; Broich et al., 2015). Observed remotely-sensed phenology patterns are the response of heterogeneous land surface conditions, integrating multiple species, age classes and canopy layers within the ecosystem (D'Odorico et al., 2015).

Satellite-based green indices, such as the Normalized Difference Vegetation Index, NDVI (Rouse et al., 1973) and the Enhanced Vegetation Index, EVI (Huete et al., 2002), represent effective proxies of vegetation photosynthetic performance by exploiting the interaction of visible light with leaf pigments, and of near-infrared (NIR) energy with internal leaf and canopy structures (D'Odorico et al., 2015). NDVI is the most common green index used to study vegetation; however, it tends to saturate over dense canopies, like forested areas, losing sensitivity (Gitelson, 2004). EVI was hence proposed as a modified NDVI, having a larger dynamic range and atmospheric and soil background correction. As a consequence, EVI is more responsive than NDVI to detect forest seasonal variations, especially for dense and large canopy background

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https://doi.org/10.1016/j.jag.2018.10.003
Received 6 August 2018; Received in revised form 28 September 2018; Accepted 3 October 2018
0303-2434/

such as broadleaved forests (Huete et al., 2014; Broich et al., 2015; Wang et al., 2017).

The time series analysis of vegetation indices allows for quantifying intra-annual changes in vegetation activity timing and intensity (Lasaponara, 2006; Balzter et al., 2007; Suepa et al., 2016; Wu et al., 2017), relating these changes to environmental processes and dynamics (Rojas et al., 2011; Bajocco et al., 2017; Bascietto et al., 2018), measuring the start, the end and the length of the growing season (Reed et al., 1994; Balzarolo et al., 2016; Baumann et al., 2017; Garonna et al., 2018), along with assessing the plant communities rhythms of growth, greening and senescing (Puppi, 2011).

The phenological timing of plant communities is regulated by the seasonal period strategic for growth and reproduction according to synchronizing (e.g. temperature, rain, frost, drought risks, topography, latitude) and asynchronizing (e.g. resource competition, seed dispersal, pollination) factors (Wheelwright, 1985; Primack, 1985). The synchronizing factors tend to homogenize the phenological behaviour of different species, such that plant communities can be identified by a characteristic phenological pattern (Puppi, 2011). Macroecological investigations have shown that similar phenological responses characterize species belonging to similar eco-regions (Thuiller et al., 2004; Chuine, 2010) due to their plastic response to some environmental conditions such as temperature, water availability or photoperiod (Chuine, 2010). Remote sensing provides ideal data to base regional vegetation phenology classifications on, since they consistently measure vegetation processes and functions in time and space (Wessels et al., 2009).

Given the huge amount of remotely sensed data, effective computing strategies are necessary to exploit the phenological information provided by long-term time series and to reduce data redundancy and processing complexity (Siachalou et al., 2015). Several studies used phenological clustering to classify pixels with an identifiable seasonal behaviour. White Michael et al., 2005 used k-means clustering in order to identify NDVI-based pheno-regions with similar vegetation phenology and climate, aiming to recognize areas with a minimized probability of non-climatic forcing for long-term phenological monitoring; Mills et al. (2011) proposed an approach (Forest Incidence Recognition and State Tracking, FIRST) based on clustering NDVI data, to provide an early warning system for differentiating between normal and abnormal phenology; Bajocco et al. (2015) derived a phenological map by hierarchical clustering homogenous territorial units of fuel in terms of seasonal NDVI Fourier harmonics; finally, Hoagland et al. (2018) derived NDVI-based pheno-classes and pheno-clusters to distinguish owl sites from random sites, and create habitat suitability maps.

Within this framework, we applied a multivariate clustering approach to a long-term MODIS EVI time-series (2001–2017) for investigating the phenological variability of forests in Italy and examining the different mechanisms of phenology response to biophysical drivers. The objectives of this study are: (i) classifying the Italian forests into phenological clusters (i.e. pheno-clusters), (ii) identifying the main phenological characteristics and the forest compositions of each pheno-cluster and (iii) exploring the role of climate and physiographic variables in the phenological timing of each cluster.

2. Material and methods

2.1. Study area

Italy is located in southern Europe, extending for about 300,000 km^2; it consists of the entirety of the Italian Peninsula and the two Mediterranean islands of Sicily and Sardinia, in addition to many smaller islands. Italy is largely surrounded by the sea, with a coastline of about 7600 km, including the islands. The country features about 23% flat zones (0–300 m a.s.l.), 42% hilly areas (300–800 m a.s.l.), and 35% mountainous regions (> 800 m a.s.l.) that are grouped in two major mountain ranges (the Alps and the Apennines). Given the longitudinal extension of the peninsula and the mountainous internal conformation, climate of Italy is highly variable. In most of the inland northern and central regions, the climate ranges from humid subtropical to humid continental and oceanic. In particular, the climate of the Po valley geographical region is mostly continental, with harsh winters and hot summers. The coastal areas of Liguria, Tuscany and most of the South is generally characterized by Mediterranean climate. Conditions on peninsular coastal areas can be very different from the mountainous inner zones, particularly during the winter months when the higher altitudes tend to be cold, wet, and often snowy. The coastal regions have mild winters and warm and dry summers. Average winter temperatures vary from 0 °C on the Alps to 12 °C in Sicily, while the average summer temperatures range from 20 °C to over 25 °C.

According to the Corine Land Cover (CLC) map of 2006, the main land uses are: agricultural lands (47.1%), subdivided into arable lands (22.8%), permanent crops (8.6%) and permanent pastures (15.7%), and forests (31.4%). The most widespread broadleaved forest categories are: *Quercus petraea*, *Q. pubescens* and *Q. robur* (12.6%); *Fagus sylvatica* (12%); *Q. cerris* and *Q. frainetto* (11.7%). Among the coniferous forests, the most common are: *Picea abies* (6.8%), *Larix decidua* and *Pinus cembra* (4.4%); *Pinus nigra* and *P. leucodermis* (2.7%); and *P. pinea* and *P. pinaster* (2.6%).

2.2. Forest types data

The Italian National Forests Inventory (INFI) was realized according to three phases of sampling. In the first phase Italy was covered by a grid of 306,831 cells, each being 1 km2 wide and a random point was selected in each cell. In the second phase, on the basis of aerial photos, the first-phase points were photo-interpreted. A set of randomly sampled points were assigned into a forest type (FT) by ground inspection if a surrounding area larger than 5000 m2 matched the same FT. In the third phase a sample of approximately 7,000 second phase-points was randomly selected and forest metrics were measured on ground (see Fattorini et al., 2006 for detail). In this work, we referred to the third phase INFI points and the forest types (FTs) considered are listed in Table 1.

2.3. Phenology data

The enhanced vegetation index (EVI) was developed to optimize the vegetation signal through a decoupling of the canopy background signal and also reducing the atmosphere effects (Huete et al., 2014; Broich et al., 2015; Wang et al., 2017). EVI is computed as follows:

$$EVI = G \text{ x } (\rho_{NIR} - \rho_{red}) / (\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L)$$

Where G is the gain factor, ρ is the surface reflectance (atmospherically

Table 1
List of the INFI forest types (FTs) analyzed.

Forest types	
CON1 - *Larix decidua, Pinus cembra*	Coniferous
CON2 - *Picea abies*	
CON3 - *Abies alba*	
CON4 - *Pinus sylvestris, Pinus montana*	
CON5 - *Pinus nigra, P. laricio, P. leucodermis*	
CON6 - *Pinus pinea, P. pinaster*	
DECB1 - *Fagus sylvatica*	Deciduous broadleaved
DECB2 - *Quercus petraea, Q. pubescens, Q. robur*	
DECB3 - *Quercus cerris, Q. frainetto, Q. trojana*	
DECB4 - *Castanea sativa*	
DECB5 - *Ostryacarpinifolia*	
DECB6 - Hygrophilous woods	
EVEB1 - *Quercus ilex*	Evergreen broadleaved
EVEB2 - *Quercus suber*	

corrected), C_1 and C_2 are the coefficients of the aerosol resistance term, and L is the canopy background adjustment. The coefficients adopted in the EVI algorithm are: $L = 1$, $C_1 = 6$, $C_2 = 7.5$, and $G = 2.5$ (Huete et al., 2002).

By means of Google Earth Engine, 16-day composite MODIS EVI images (MOD13Q1-v006 product) were acquired from 2001 to 2017: 23 images per year, from 1st of January (EVI_01) to 19th of December (EVI_23). Each composite image was filtered to exclude pixels covered by clouds and possible shadows according to the MODIS pixel quality layer (quality assurance, QA = 1) (Didan, 2015). Given the coarse MODIS EVI spatial resolution (pixel size of 250 m) with respect to the INFI points and the possible mismatch between the two datasets, we applied two filters to the INFI points. To reduce the probability of including in our study non-forested/ambiguous points, a first filter has been applied with the aim to consider only the INFI points falling in large forested areas (i.e. excluding small, heterogeneous, edge- or non-forested areas). The INFI points were hence intersected with the 2006 CLC map of Italy by means of ArcMap (ESRI, 2009). The CLC map is based on Landsat satellite images, with a scale of 1:100,000, minimum mapping unit of 25 ha, and minimum polygon width of 100 m (EEA, 2007). The standard CLC nomenclature follows a three-level hierarchy; only the INFI points belonging to the third-level CLC class "Forests" were kept for further analysis. Secondarily, all the INFI points with at least one EVI temporal band value lower than or equal to zero, were removed in order to reduce the probability of including zones with e.g. bare soil or water, to consider only densely forested pixels, as well as to avoid areas totally or mostly covered by snow. The remaining dataset was made up of 4640 points, and for each point we computed the 18-year mean EVI temporal profile. It is to be considered that, in areas subject to extreme disturbances and high environmental variability, the median is a better representation of central tendency than the mean.

2.4. Data analysis

To compute the phenological separation among the different forest types, we carried out a Discriminant Function Analysis (DFA) on the 4640 INFI points. The DFA is an ordination method, similar to Principal Component Analysis (PCA), which examines whether significant differences exist among the categorical response variables (forest types) according to a given set of predictors (23 mean EVI temporal bands) (Moore, 2013). The DFA determines the variable best combination so that the first DFA factor specifies the main discrimination among groups (in terms of variance inter-groups), the second represents the second most important one, and so on. Being the factors orthogonal, their contributions to the discrimination among groups do not overlap.

Then, to identify groups of different forest types with similar seasonal timing (i.e. pheno-clusters - PhCs), we carried out a k-Means (kM) clusters analysis on the 4640 INFI points based on the values of the first two DFA factors. The kM is a type of unsupervised machine learning method that works iteratively. The aim of kM is to retrieve *k* groups in the data based on variables similarity (MacQueen, 1967). In this work, the optimal *k* number, i.e. the number of clusters which allows the most significant phenological discrimination among INFI points, was chosen according to the highest value of the cubic clustering criterion (Sarle, 1983).

To analyse the association between the pheno-clusters and forest types, we first created a two-way contingency table in which the INFI points were assigned to the corresponding PhCs and FTs (see Bajocco et al., 2010). The strength of association between pheno-clusters and forest types was then measured through a permutational chi-square (χ^2) test, by comparing the observed values of χ^2 to 9999 random values of χ^2 under the null hypothesis of no association between pheno-clusters and forest types.

Finally, to understand the role of the main biophysical drivers in the phenological discrimination of the INFI points, we analyzed the correlation of a set of bioclimatic variables, latitude and elevation (Table 2)

Table 2
List and description of the selected bioclimatic variables.

Acronym	Description of the variables
Tmean	Annual Mean Temperature (°C)
IsoT	Isothermality, i.e. ratio between mean diurnal range and temperature annual range *100 (%)
Tseas	Temperature Seasonality, standard deviation *100 (%)
Tcold	Mean Temperature of Coldest Quarter (°C)
Ptot	Annual Precipitation (mm)
Pseas	Precipitation Seasonality, i.e. coefficient of variation (unitless)
Pdry	Precipitation of Driest Quarter (mm)
Lat	Latitude in UTM projection (m)
Elev	Elevation a.s.l. (m)

with the first two DFA factors. The bioclimatic variables were derived from the WorldClim V2 dataset (http://www.worldclim.org/bioclim) which is a set of 1970–2000 global climate layers (monthly gridded temperature and precipitation data) with a spatial resolution of 1 km^2.

According to Table 2, the selected bioclimatic variables indicate annual trends (e.g., Tmean, Ptot), seasonality (e.g., Tseas and Pseas), and extreme or limiting environmental variables (e.g., Tcold, and Pdry) (Hijmans Robert et al., 2005; Fick Stephen and Hijmans Robert, 2017). The elevation was extracted from the ASTER Global Digital Elevation Model (GDEM) V2 product; it has a 30 m spatial resolution and is freely available at https://asterweb.jpl.nasa.gov/gdem.asp. A Pearson correlation analysis between the selected biophysical driving variables and the DFA factors was then performed to identify the contribution of each variable to the phenological discrimination. The temporal discrepancy between the bioclimatic and MODIS data may be overcome because any patterns of change in the mean values may be trivial given the inertia of vegetation, as well as the main regional climate drivers (i.e. latitude and elevation) and the coarse expectations of the analysis.

All the statistical analysis were performed by means of XLSTAT software package (https://www.xlstat.com).

3. Results

The first two DFA factors explained the 71.65% of the total variance inter-groups in the phenological ordination space of the considered forest types. Fig. 1 shows that there is a clear phenological separation among the majority of the forest types belonging distinctively to the four quadrants of the DFA biplot. In the same figure, it is also shown the contribution of the EVI temporal bands to the first two DFA factors: the first factor (F1), explaining the 43% of the total variance inter-groups, is an expression of a seasonality gradient going from winter (i.e. EVI_01-06 and EVI_22-23) to summer (i.e. EVI_09-18), and vice versa (i.e. the deciduousness); as a consequence, the DECB types are all located in the positive part of F1 (high summer greening), while the EVEB and the CON types are distributed across the negative part of F1 (high winter greening). To the contrary, the second factor (F2), explaining the 28% of the total variance inter-groups, reflects the annual productivity, mainly determined by spring and fall EVI values (i.e. EVI_07-08 and EVI_19-20); as a consequence, the most year-long productive FTs are located around the positive part of F2. It is to be noticed that high EVI values in spring and fall indicate a longer growing season, that hence characterizes all the FTs distributed in the positive part of F2.

In detail, there is a clear phenological separability between CON6, EVEB1 and EVEB2 and the deciduous forest types along the first DFA factor: the former forest types (typically Mediterranean) show the highest productivity performance in winter and the lowest in summer; while the latter ones (typically Temperate) are characterized by high summer greening activity and winter dormancy. The CON1-CON4 forest types, on the contrary, show an intermediate phenological behaviour between the Mediterranean and the deciduous FTs. Such evidence is mainly due to the phenological characteristics of the high-

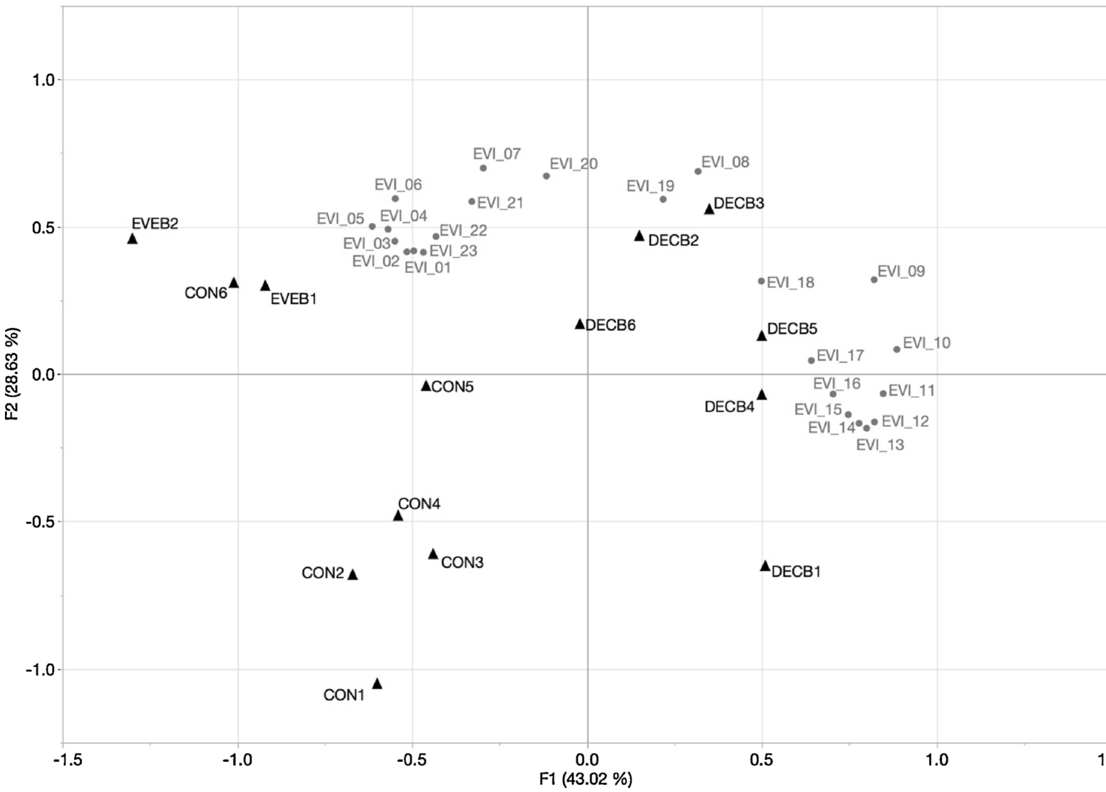

Fig. 1. Discriminant Function Analysis (DFA) biplot: distribution of the forest types centres of gravity (black) and of the 23 EVI temporal bands (grey) according to the first two DFA factors.

elevation coniferous forests, with moderately high summer greening activity, but low remotely-sensed winter productivity, also because of very low EVI values due to residual snow cover. Noticeably, there is a high phenological separability even within the deciduous FTs: DECB1 clearly discriminate from DECB2 and DECB3 along the second DFA factor, highlighting the wider growing season of the latter forest types that is largely active also in spring and fall. The CON5, DECB4, DECB5 and DECB6 do not show a clear separation from the other FTs; phenologically, they represent transitional forest types.

The k-Means analysis produced four distinctive phenologically homogeneous macro-clusters, namely pheno-clusters. Fig. 2 shows the distribution of the INFI points belonging to the different PhCs across Italy, while Fig. 3 shows the elevation gradient followed by the pheno-clusters, ranging from the higher elevations of PhC1 to the lower of PhC4.

Fig. 4 shows the EVI temporal profile typical of each pheno-cluster, highlighting that PhC2 and PhC3 are the pheno-clusters with the highest seasonal variability of EVI profile, while the PhC4 EVI curve is less variable during the year. PhC2 has the lowest values during the winter months, and PhC4 has the lowest values during the summer peak, while PhC1 represents the pheno-cluster with the lowest productivity over the year.

The permutational chi-square (χ^2) test between FTs and PhCs gave an observed value of $\chi^2 = 5478.050$ ($p = 0.0001$). This result proves a high degree of association between forest types and pheno-clusters in Italy. Positive association (or correlation) between two classes indicates a high probability of co-occurrence, while negative association means a high probability of reciprocal avoidance. According to Table 3, the CON1 – CON4 forest types resulted positively associated with the PhC1 ($p = 0.05$), that represents the “High-elevation coniferous” phenological type. The DECB1 and DECB4, typical of mountainous zones, were positively correlated with the PhC2 ($p = 0.05$), that can be considered the “High-elevation deciduous” phenological type. The DECB2, DECB3, DECB5 and DECB6, typical of the lower mountain belts, showed the highest positive association with the PhC3 ($p = 0.05$), that represents the “Low-elevation deciduous” phenological type. Finally, CON5, CON6, EVEB1 and EVEB2 proved to be positively correlated to the PhC4 ($p = 0.05$), that represents the “Mediterranean evergreen” phenological type.

To analyse the role of the driving variables in the pheno-clusters separation, the correlation coefficients of the driving variables were plotted over the DFA factors plane together with the centres of gravity of each pheno-cluster (Fig. 5). The joint plot showed a clear biophysical characterization of the different pheno-clusters: the precipitation seasonality (major contributor to F1) is the main driver for both the “Mediterranean evergreen” and the two “deciduous forests” phenological types in opposite ways; while the elevation (major contributor to F2) is the key variable for the “High-elevation coniferous” and the “High-elevation deciduous” types.

4. Discussion

Several studies have found that plant species phenology regional patterns are typically correlated to environmental parameters such as temperature, precipitation, latitude or elevation (Santamarĺa et al., 2003; Caicedo et al., 2004; Zu et al., 2018; Workie and Debella, 2018). Other studies detected variations in the remotely-sensed vegetation phenology, attributing them to biotic (e.g. leaf out, browning) and/or abiotic variables (e.g. snow occurrence, frost cover) (Jin et al., 2017; Bascietto et al., 2018). In this framework, the identification of pheno-regions or pheno-clusters (i.e. areas or groups of different plant types of homogeneous phenological response) represents a key tool for the detection of environmental patterns and global change warnings (Cleland et al., 2007; Parplies et al., 2016).

This study allowed to identify the most common phenological patterns for the forested areas of Italy and their relationship with the main biophysical drivers, as well as to investigate the ability of the EVI temporal bands in discriminating each pattern detected. Results

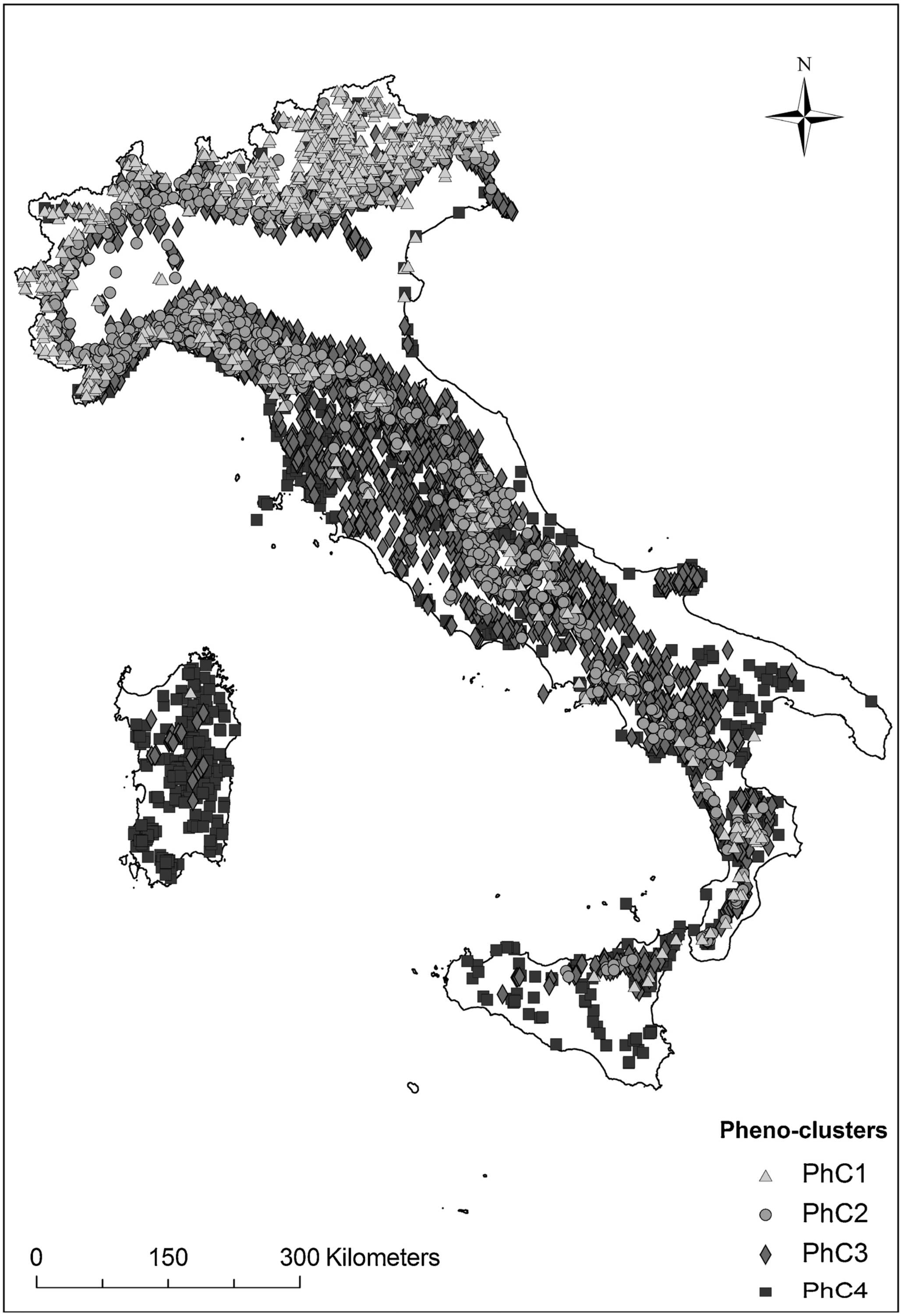

Fig. 2. Distribution of the Italian National Forests Inventory (INFI) points per pheno-cluster across Italy.

identified four main phenological types of forests; the obtained pheno-clusters showed to follow a clear elevation gradient, with a distinct separation of the forest phenological groups along the Temperate-to-Mediterranean climatic transition in Italy:

- the "High-elevation coniferous" type (PhC1), mainly composed by *Larix decidua*, *Pinus cembra*, *Picea abies* and *Abies alba*. It is located in the mountainous, inner areas, and mainly correlated to very high elevations and high latitudes. The consequent unfavourable environmental conditions of very low winter temperatures and short day-light duration determined a phenological type characterized by a low total annual productivity. Considering that this PhC is mainly an evergreen-type cluster (apart from *Larix decidua*), the observed annual variability may be the result of a combination of snow-cover (Jönsson et al., 2010) and growth/senescence cycle of annual or perennial groundcover vegetation (or deciduous trees) interspersed with the evergreens;

- the "High-elevation deciduous" type (PhC2), mainly composed by *Fagus sylvatica* and *Castanea sativa*. It is located in the mountainous, inner areas, and principally correlated to high latitudes, low

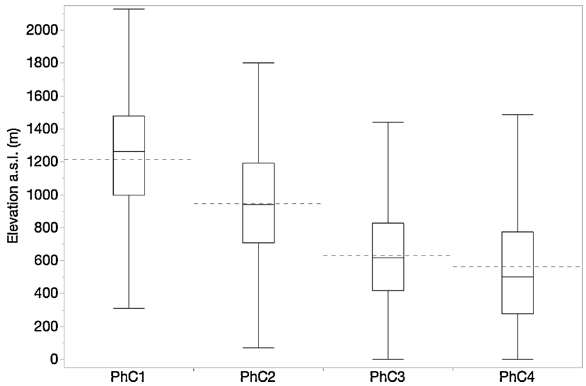

Fig. 3. Boxplot of the elevation of each pheno-cluster. The dashed lines represent the mean elevation.

precipitation seasonality, but abundant summer rainfalls, low isothermality and high temperature seasonality, with low minimum temperature values. The environmental conditions of wet summers and harsh winters determined a phenological type characterized by high total annual productivity and very high seasonality, with a peak of productivity in summer;

- the "Low-elevation deciduous" type (PhC3), mainly composed by *Quercus petraea, Q. pubescens, Q. robur*, *Q. cerris* and *Q. frainetto*. It is located in the hilly areas, from the inner zones to the coasts, and mostly correlated to medium-low elevations and moderate summer precipitations and annual mean temperatures. The environmental conditions of quite wet summers and cold winters determined a phenological type characterized by very high total annual productivity and medium-high seasonality with a growing season longer than the "High-elevations deciduous" type;

- the "Mediterranean evergreen" type (PhC4), mainly composed by *Quercus ilex*, *Q. suber* and by *Pinus pinaster* and *P. pinea*. It is located in the flat-hilly, coastal areas, and principally correlated with high precipitation seasonality, high summer drought, low latitudes, high isothermality and high mean annual temperatures. The environmental conditions of mild and wet winters together with hot and dry summers determined a phenological type characterized by a year-long productivity and very low seasonality due to the evergreening adaptation characteristics of the forest types comprising this pheno-cluster. It is to be noticed that this is the most taxonomically heterogeneous cluster, including both broadleaved and coniferous FTs, and it may represent a combination of forest types with different leaf adaptation, but similar drought-driven phenology.

These evidences showed two strong environmental gradients in the forest types distribution across Italy captured by the pheno-clusters. The first gradient is related to climatic influences and correlated with intra-annual variation of summer precipitation and minimum winter temperature. Along this gradient the central and northern regions were characterized by productivity values correlating with high summer and spring precipitation. The southern regions on the other hand were distinguished by high productivity, with small fluctuations mainly related to summer drought. This complies with the general perception of phenology-climate dependency and confirms that the yearly cyclic dynamism of vegetation growth and the productivity of vegetation during this period are ecosystem functional indicators that are mostly dependent on seasonal precipitation and temperature patterns (Ivits et al., 2013). The climatic data are associated with the F1 that only explains 43% of the variance in the remotely-sensed phenological discrimination, suggesting that productivity and phenological variables indicate a pattern in the forest ecosystems gradient that climate alone cannot explain. The second gradient is related to the geophysical variables like elevation and latitude, which, unlike climate, represents the unchanging drivers. They are associated to the F2 that explains about the 28% of the variance in the remotely-sensed phenological discrimination. This suggests that these parameters capture ecosystems functional dynamisms that the climate data cannot directly guide, and that can be related to other influencing variables like e.g. exposition, snow persistence, management or soil characteristics.

The major potentiality of the proposed approach is the ability to go beyond the structural characteristics of forests and looking at their functional aspects. According to the structural categories, the coniferous group includes both alpine and Mediterranean coniferous; the deciduous broadleaved does not consider any internal separation; and the evergreen broadleaved does not include other types of leaf physiologies than the sclerophyllous; in this kind of classifications, the

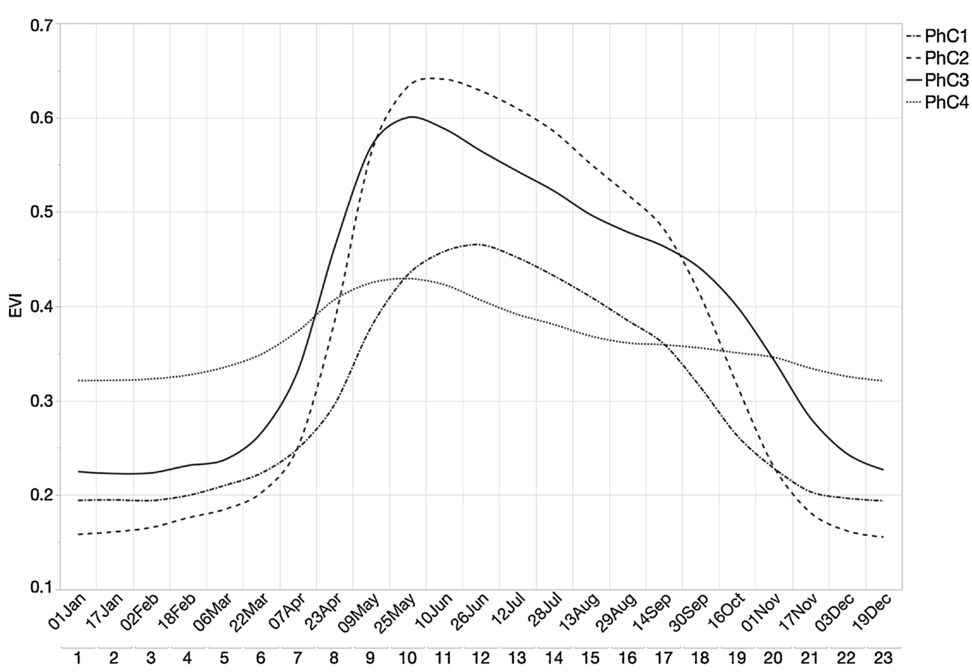

Fig. 4. Mean EVI temporal profile of each pheno-cluster.

Table 3
Contingency table showing the number of INFI points shared between the pheno-clusters and forest types. Grey cells indicate a positive association between the pheno-clusters and forest types, whereas normal characters denote a negative association. All values are significant at the p = 0.05 level, except those with ^{NS}.

		Forest types														
		CON1	CON2	CON3	CON4	CON5	CON6	DECB1	DECB2	DECB3	DECB4	DECB5	DECB6	EVEB1	EVEB2	Tot
Pheno-clusters	PhC1	77	218	72	95	78	8	73	9	9	14	9	18 ^{NS}	14	0	**694**
	PhC2	11	37	17	20	25	4	479	62	82	280	167	33 ^{NS}	6	0	**1223**
	PhC3	1	13	13	19	64	41	108	400	504	241 ^{NS}	335	77	53	2	**1871**
	PhC4	0	26	8	19 ^{NS}	103	139	2	71	29	22	12	27 ^{NS}	296	98	**852**
	Tot	**89**	**294**	**110**	**153**	**270**	**192**	**662**	**542**	**624**	**557**	**523**	**155**	**369**	**100**	

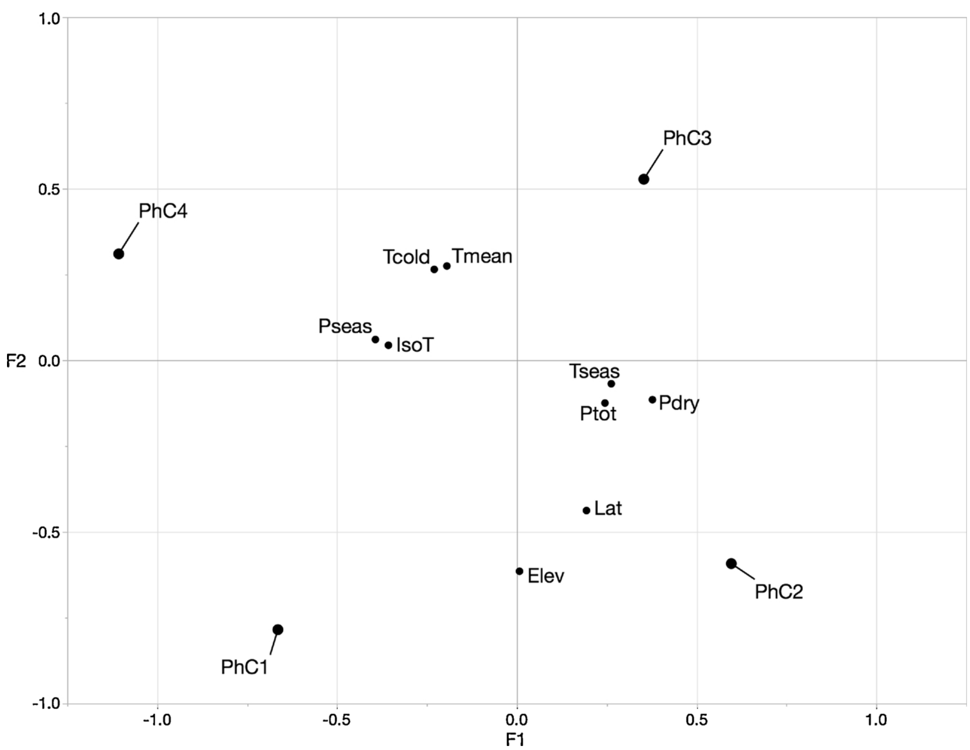

Fig. 5. Plot of the correlation coefficients of the driving variables, together with the corresponding centres of gravity distribution of each pheno-cluster, into the DFA factors (F1 and F2) plane.

processes characterizing the functioning of the different categories are overlooked. The phenological grouping, to the contrary, represents a process-based approach including forest types that, although belonging to different structural categories, have similar timing, are characterized by the same phenological moments, and driven by the same biophysical variables. Such an approach provides valuable information on forest ecological functionalities with repercussions in terms of e.g. understanding of the converging climate adaptation of different forest species, localization of the ecological niche at large scale, recognition of phenological responses to environmental stress, identification of the common carbon cycling phases for different forest species belonging to the same phenological group, development of *ad hoc* practices to fight forest fires and manage fuel load and flammability, ecological framework to be considered when developing forest inventory strategies. Furthermore, the proposed methodology represents a no-cost, time-saving and replicable method at any ecosystem level.

In conclusion, quantifying the vegetation biophysical characteristics, independently from taxonomic or phylogenetic linkages, may open new perspectives for exploring plant functional properties (Ustin Susan and Gamon John, 2010). In this view, several studies (Westerling, 2016; Anav et al., 2017; Bajocco et al., 2017; Mountford et al., 2017; Garonna et al., 2018; Vrieling et al., 2018) are currently going beyond the use of phenology as merely a support tool, considering phenology more and more as a self-explained science. The availability of time-series satellite products has enabled a reliable investigation of seasonal patterns dynamics that is expanding the concept of vegetation functional types, proposing phenology as a new phytogeographic framework for large-scale environmental studies.

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