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Correlation of Vegetation and Air Temperature Seasonal Profiles – Spatial Arrangement and Temporal Variability

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1. Introduction

The existence of a strict link between land cover annual cycles and seasonality in the meteorological variability is well known. Joint observations have been exploited for thousand of years as an efficient basis for the empirical land management in agriculture. In Europe, the first attempt to catalogue detailed records of seasonal weather and vegetation phenological events was made by the Marsham family in early 1700s but only during the 19th century this activity become more systematic in the attempt to collect records for wide scientific utility (e.g., Sparks & Carey, 1995).

More recently, the large diffusion of satellite observations has enabled direct monitoring of the land surface at repetitive time intervals and over extended areas. They have proven to be cost effective tools and are expected to contribute to a wide array of local/global change-related applications (vegetation and ecosystem dynamics, hazard monitoring, land surface climatology, hydrology, land cover change etc.) (see e.g. EU Global Monitoring for Environment and Security - GMES, 2010). Mainly thanks to these observations, today's researchers can investigate many problems related to atmosphere-biosphere interactions and physiological responses of vegetation to climate change. In particular, vegetation cover phenology is attracting much attention both for the intrinsic interest in studying collective behaviours of plant communities in specific geographic and anthropic contexts (e.g., Ting et al., 2008) and for understanding their link with climatic variability (e.g., Viña and Henebry, 2005; Maignan et al., 2008; Normand et al., 2009; Maselli et al., 2009; Ma and Zhou, 2011).

Changes in climate can alter land cover phenology both directly, by modifying timing and amplitude of phenological profiles (e.g., Menzel et al., 2001; 2006; Penuelas and Filella, 2001; Cleland et al., 2007; Prieto et al., 2009) and indirectly, by affecting the plant community distribution and dynamics (Feehan et al., 2009). In turn, modifications in the vegetation

phenological cycle imply alteration in the exchanges with the atmosphere and particularly in the Carbon balance (e.g., Piao et al., 2008).

Unfortunately, heterogeneity over a wide range of scales severely limits the characterization of biosphere-atmosphere interactions (e.g. Göckede et al., 2009; Zhao et al., 2009). The approximation of ecosystems by considering the prevailing plant functional type (PFT) is too rough for many applications since a high percentage of the terrestrial biosphere is actually made by highly intermixed PFT compositions (Bhreshears, 2006) and new aggregation concepts are required for describing functional categories (Williams et al, 2009; Ustin and Gamon, 2010). Therefore, it is necessary to reduce details without destroying information of dynamical value, especially in regions characterized by a mosaic of human land use and natural vegetation whose role in local and global dynamics is crucial, as shown by recent studies on the repercussions of land-use/land-cover modifications on the climate system (e.g., Pielke, 2005; Douglas et al, 2009; Zhao et al., 2009; Mahmood et al., 2010).

In this Chapter we approach the estimation of the monthly correlation between land surface phenological cycles and seasonal air temperature patterns in order to investigate how this correlation is distributed in space and how this distribution varies in the passage from a year to another one. We refer to "land surface phenology" rather than to "vegetation phenology", according to the remote sensing community (deBeurs & Henebry, 2005), because the variability observed at the pixel detail is the integrated effect of a mixing of signals, derived from extended plant aggregations and non vegetated traits. However, it is widely recognised that satellite data, by means of suited vegetation indexes, are able to capture collective behaviours of plant communities adapted to the specific climatic, structural, and ecological characteristics of the geographical area.

In order to investigate the spatial and temporal variability of vegetation and temperature in a typical, very complex, Mediterranean environment, we analyze monthly NDVI (Normalized Difference Vegetation Index) and air temperature time series over Southern Italy, core of Mediterranean Basin, where the responsiveness of vegetation to temperature increase is the greatest in the European continent (e.g. Estrella et al., 2009).

Heterogeneity is reduced by looking for phenological alikeness, as it appears at the sensor resolution, since this reflects analogies in the collective functionality of the sub-pixel components. Profiles of monthly NDVI, acquired by the MODIS sensor (250m), are elaborated by performing a multitemporal clustering on annual basis to aggregate areas with similar phenological cycles. In the same way, areas with common phenological and temperature seasonal patterns are analyzed by classifying temperature and NDVI profiles jointly. In order to evaluate the spatial variability in the phase-relation between vegetation and temperature, temporal correlations are estimated per pixel and gathered in a correlation map (r-map), which is created per each year. Sign and magnitude of the correlation coefficient inform us about the phase relation between the annual patterns: high positive values of r characterize areas where phenology and temperature are nearly in phase; whereas high negative values characterize areas where they have about opposite phases. Thus, the r-map provides a measure of the similarity between phenology and temperature profiles and a representation of the spatial distribution of such a similarity. This should point out leading spatial structures dominated by analogous biogeographical features. In addition, the comparison between r-maps estimated for different years should enhance the

influence of inter-annual meteorological fluctuations on such structures thus discriminating stable regions from more variable areas where the dependence of phenology on temperature seasonality varies with meteorology.

2. Study area

The area under study belongs to the Mediterranean biogeographical region and is located in the Southern part of the Italian peninsula (Fig. 1). Its territory is mainly mountainous: the Apennine chain runs along the peninsula from NW to SE, splitting it in two parts and forming a broad irregular mountain system with generally narrow coastal plains on both sides (Fig. 2a). In particular, the East side, overlooking the Adriatic Sea, is characterized by level areas such as most of the Apulia region and the plains lying in the far south-east. The west side, overlooking the Tyrrhenian Sea, is characterized by an orography more complex than the other: uplands and plains stretch along the west coast between the Apennines and the sea. This region includes a number of major cities, among which there are Naples and Palermo. The Strait of Messina separates Sicily, the largest island in the Mediterranean Sea, from mainland Italy. Much of the northern portion of the island is mountainous, and Mount Etna, one of the largest active volcanoes in the world, reaches 3000 m in altitude.
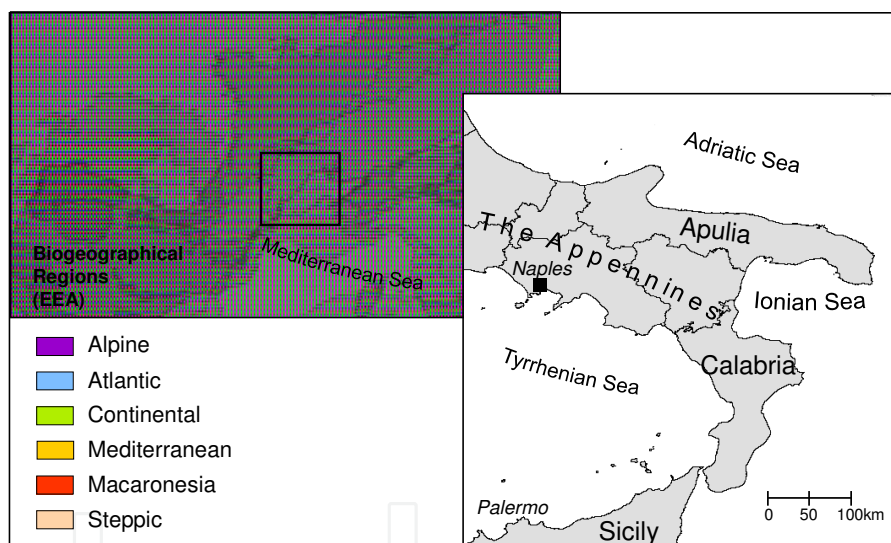

Fig. 1. Location of the study area within the map of biogeographical regions (source European Environment Agency-EEA) and the administrative limits of the investigated areas with the principal placenames.

Altogether, Southern Italy enjoys a mild climate thanks to its position in the middle of the Mediterranean, to the influence of air masses coming from North Africa, and to the presence of the barrier formed by the Alps chain that shelters from the northern cold winds. Nevertheless, local significant differences are present, especially due to latitude variability (~6⁰), to orography, and to the maritime climate of the coasts. In particular, its rich orographic variability makes this territory a good test site for assessing the effect of altitude on phenology. In the inland areas, where the sea effects are negligible and altitude is high, climate is typically mountainous with cold winters. On the Adriatic side, the thermoregulatory action of the sea is reduced by the eastern cold and humid winds. The

seaboard and the southernmost zones have a typical Mediterranean climate, characterized by rainy autumns and winters, and very warm dry summers. Gathered rain events often trigger floods and erosion. The areas of Calabria well synthesize the high basic heterogeneity of the territory. Here, we can find typically sub-tropical coastal environments opposed, at a distance of few tens of kilometers, to typical alpine mountain environments, such as those of the Sila National Park. Agriculture is the main economic activity in Southern Italy. Cereal monocultures are prevalent and farmlands as well as pastures are widespread on the territory (Fig. 2b), also at relatively high altitude. Industrial activities and urban settlements are mainly distributed according to orography: main cities and industrial areas are prevalently located along the coast. Inland, the industrial sector is less developed, so there are only small factories. Although natural vegetation is present along the coast (pine forests and maquis prevalently), it predominates at high altitude, where broad leaved forests and maquis are densely distributed.

Degradation signatures are evident in the southernmost part of the territory, where any climatic change involving increase of drought duration and/or intensity of rare rainfall events can favor vulnerability to degradation (Lanfredi et al., 2003). Since also agricultural practices often are obsolete and not accompanied by suited soil preservation strategies, desertification could be expected in some areas (Sciortino et al., 2000; Liberti et al., 2009; De Santis et al., 2010).

3. Data

3.1 Satellite data

To evaluate the cycles of vegetation activity, we analyzed a vegetation index time series acquired by the MODIS sensor. In particular, we elaborated monthly mean values of NDVI (Normalized Difference Vegetation Index) at full spatial resolution (250m) for the period 2005-2008. NDVI data, available as 16-day composite, were gathered from the MODIS dataset by NASA LP DAAC (Land Processes Distributed Active Archive Center).

The selected index is related to the structural and functional characteristics of vegetation cover, since it is based on the difference of reflectance responses in the red and near infrared bands. The index ranges between -1 and +1; negative values are linked to water and thick clouds, low positive values to bare soils, high positive values represent dense and photosynthetically active vegetation. NDVI is adopted as proxy for photosynthetic activity to characterize vegetation dynamics. In particular, MODIS-NDVI time series are widely analyzed to study land surface phenology in both natural environment and cultivated covers (e.g., Butt et al., 2011; Jönsson et al., 2010; Karlsen et al., 2008).

3.2 Orographic data

The analysis of the dependence of phenology on altitude was performed by using a Digital Elevation Model (DEM) derived by the NASA SRTM (Shuttle Radar Topographic Mission). The original data available as 3 arc second (~90m pixel resolution) were reprojected to satellite data projection and resampled using an average filter to 250m (Fig. 2a) to make them comparable with MODIS data.

3.3 Temperature maps

We used temperature data collected by national networks distributed over Southern Italy. In particular, maps of air temperature at 250m resolution were obtained from ground station measurements by means of a combined deterministic-stochastic model suitably devised for the study region on the basis of latitude, elevation (from the re-sampled SRTM DEM), and sea distance as independent variables (Coppola et al., 2006). Data to implement the spatialization model were obtained from 15 years daily temperature time series (1994-2008) collected at 35 stations of the Central Office of Agrarian Ecology – National Agronomic Network (UCEA-RAN). The model coefficients were used to elaborate the maps of monthly mean temperature (hereafter T) for the period 2005-2008.

3.4 Land cover data

Land cover information was extracted from the Corine map downloaded from the High Institute for Environment Protection and Research (ISPRA, former APAT). For the purpose
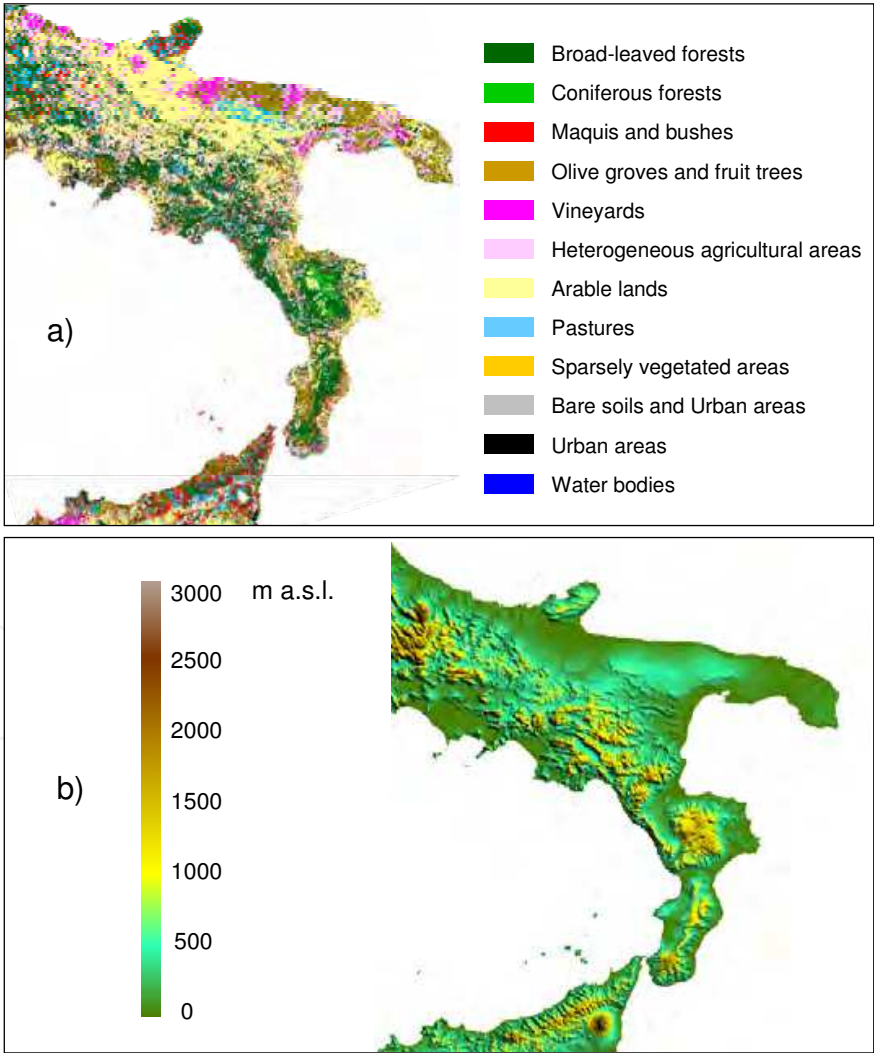
Fig. 2. Land cover map (a) obtained by recoding the Corine classes; and Digital Elevation Model (b) derived from SRTM.

of this study, the original Corine level 1-3 codes (http://sia.eionet.europa.eu/CLC2000 /classes) were reclassified to group artificial surfaces and water bodies and to preserve detailed information on vegetated covers (Fig. 2b); the adopted map has the following 12 classes: Broad-leaved and mixed forests, Coniferous forests, Maquis and bushes; Sparsely vegetated natural areas, Pastures, Arable lands, Vineyards, Olive groves and fruit trees, Heterogeneous agricultural areas, Bare soils, Urban and Industrial Areas, and Water bodies. The Corine data in vector format were rasterized in a map at the same resolution (250m) of vegetation indices.

4. Classification procedure for the identification of phenological classes

In order to group pixels on a phenological basis, we adopted an unsupervised classification since no a priory knowledge was available for pattern identification. We classified NDVI and T images at the sensor resolution (250m) by means of fuzzy k-means unsupervised algorithm, which represents an extension of the widely adopted k-means by evaluating the probability of a point to belong to a cluster instead of hard cluster identification (e.g., Richards & Jia, 2006). We selected the fuzzy approach since we do not expect abrupt variations between one phenological cluster and another one; instead, especially for natural vegetation, we can expect gradual differences among phenological patterns. In this context, the fuzziness concept can be more appropriate than an abrupt partition (e.g., Simoniello et al., 2008).

In general, this clustering algorithm groups the multispectral data according to statistical properties of their spectra for obtaining land cover/land use information (e.g., Richards & Jia, 2006). Thus, each image pixel is represented as a point in the n-dimensional space, where the n dimensions are the spectral bands and the coordinates are the brightness values in each band. Iteratively, the algorithm evaluates the probability of each point to belong to a cluster (degree of membership) starting from the primary cluster prototypes. For each iteration, the cluster prototypes are rearranged and the membership degree recomputed until the movements of cluster prototypes for successive iteration is less than a predetermined threshold. Finally, a data point is assigned to the cluster with the highest membership degree.

In this study, we applied the fuzzy k-means algorithm to the temporal domain by classifying NDVI from April up to September (period of maximum phenological variability) to avoid cluster aggregations driven by residual clouds or hardly filtered NDVI data. This seasonal period was selected just to minimize non vegetated effects on the identification of the main phenological areas; the successive analyses were instead obtained by considering the complete annual profiles. We used the Euclidean distance for computing the membership degree among patterns and fixed to 1% the minimum threshold of centroid movement, which means a variation on the second decimal figure of the NDVI value.

Although phenology is mainly driven by land cover type, we also included temperature patterns in the analysis because climatic conditions can significantly affect the phenological development for the same cover type. Thus, we jointly classified NDVI and T; for such an implementation, each pixel was represented as a point in a 12-dimensional space, where the 12 dimensions are the 6+6 monthly images of T and NDVI and the

coordinates are the values of two variables. The results of two clustering procedures (NDVI alone and NDVI-T) were compared in order to evaluate the ability of NDVI to account also for temperature.

5. Spatial structure analysis

The spatial variability of phenological aggregates was evaluated by analyzing some peculiar indices commonly adopted in Landscape Ecology analysis (e.g., Diaz-Varela et al., 2009; Fischer and Lindenmayer, 2007; McGarigal et al., 2002). We evaluated the indices described in the following on the four landscapes represented by the phenological classifications related to the investigated years (2005-2008). In particular, we analyzed:

- Number of patches, which is a simple measure of the extent of subdivision or fragmentation in a landscape.
- Mean patch size, which is the average area of patches comprising a landscape mosaic; it is perhaps the single most important and useful piece of information contained in the landscape having a great deal of ecological utility.
- Aggregation Index (AI) is equals the number of like adjacencies involving the corresponding class, divided by the maximum possible number of like adjacencies involving the corresponding class, which is achieved when the class is maximally clumped into a single, compact patch; multiplied by 100 (to convert to a percentage). AI increases as the landscape is increasingly aggregated from 0 to 100, on the basis of the following formula

$$AI = \frac{g_{ii}}{\max - g_{gg}} 100 \tag{1}$$

where, g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i; and max-g_{ii} = maximum number of like adjacencies between pixels of patch type.

- Intersperion and Justapposition index (IJI) evaluates the observed interspersion over the maximum possible interspersion for the given number of patch types. IJI approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI = 100 when all patch types are equally adjacent to all other patch types,(i.e., maximum interspersion and juxtaposition):

$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right)\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5\left[m(m-1)\right]\right)} 100 \tag{2}$$

where, e_{ik} = total length of edge in landscape between classes i and k; E = total length of edge in landscape, excluding background; and m = number of classes present in the landscape.

- Shannon's diversity index is a popular measure of diversity in community ecology, applied to landscapes. ShDI = 0 when the landscape contains only 1 patch (i.e., no diversity). ShDI increases as the number of different patch types (i.e., patch richness,

PR) increases and/or the proportional distribution of area among patch types becomes more equitable.

$$\text{ShDI} = -\sum_{i=1}^{m}(\text{PlnP})$$ (3)

where, Pi = proportion of the landscape occupied by class i.

6. Results

In order to evaluate the optimal number of clusters *n* to represent the heterogeneity of the investigated territory, we considered the trade-off between the efficacy of ecosystem representation and local fragmentation effects. A low number of classes enabled us just to distinguish natural from managed covers; whereas a high number of classes (*n*>10) put into evidence very small clusters (*n*<2% of the total pixels) arisen from the fragmentation of the edges of the dominant clusters, making the identified cluster less representative of collective dynamics. These additional clusters are not representative of extended collective dynamics. They are expected to account for that heterogeneity we would like to reduce. On this basis, we selected *n*=10 to obtain a phenological segmentation of the territory from the classification of the NDVI temporal profiles.

A second sequence of clustering maps (*n* from 2 to 30) was elaborated by jointly classifying NDVI and temperature profiles. We obtained very similar arrangements, with the differences between the NDVI and the NDVI-T clustering maps that tend to increase with *n*. Such differences are however very small; in particular, for the selected 10 classes we found no variations in the mean phenological profiles and differences in their spatial arrangement less than 0.5% (Tab. 1).

On the whole, NDVI and NDVI-T provide the same territorial segmentation. Such a similarity confirms the strong role of temperature in the vegetation development and the capability of NDVI to account for such temperature-vegetation interaction.

Cluster	1	2	3	4	5	6	7	8	9	10
Difference (%)	0.08	0.21	0.12	-0.46	0.33	-0.13	-0.39	-0.01	0.17	0.08

Table 1. Percentage difference (on the total number of pixels) between the number of pixels obtained by classifying in 10 clusters the NDVI profiles alone or the NDVI and temperature profiles together.

6.1 Characterization of phenological classes

The phenological clusters obtained by classifying on annual basis the NDVI profiles show a very coherent structure in both the spatial and temporal domains (Fig. 3). Their temporal patterns are organized in a continuum of phenological curves, which start from the early peaked curves of clusters 1 and 2, then become ever smoother up to the quite flat profile of cluster 5, and finally reach the highest summer values of clusters 10.

The spatial arrangement strongly reflects the land cover spatial distribution and the orography iso-level curves (compare Fig.2). From the lowest to the highest cluster number, there is a reduction of covers related to anthropic activities and an increase of natural vegetation (Fig. 4). In particular, the first two clusters are dominated by arable lands generally non-irrigated; then, clusters 3 and 4 also include a high percentage of annual crops but they are mainly associated with olive groves and complex cultivation patterns, with a higher percentage in the first one. In clusters 5, olive groves and vineyards are prevalent similarly to cluster 6, where also fruit trees are present. Starting from cluster 7, the presence of natural vegetation increases and also in lands principally occupied by agriculture there are significant areas of natural vegetation (Corine code 2.4.3). The cluster sequence 8-9-10 reflects the typical spatial coherence and organization of natural ecosystems in this area, i.e. the presence of transitional vegetation around the core of forested areas. In particular, the core of forests (cluster 10) is largely composed by broad-leaved trees (more than 75% of the cluster).
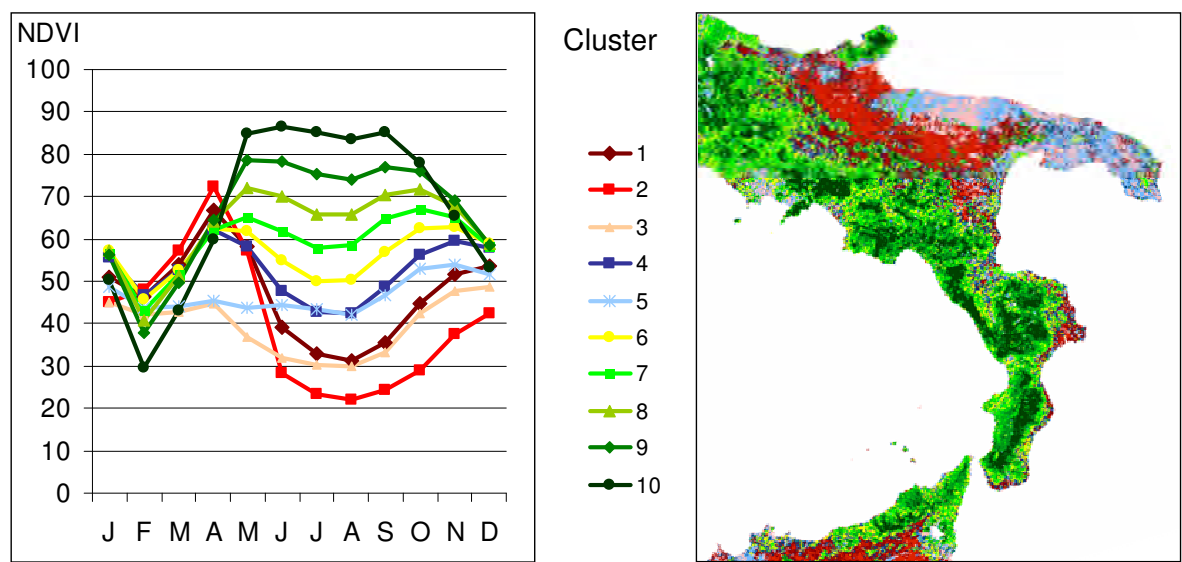
Fig. 3. Phenological profiles obtained by the fuzzy k-means classification on 2005 MODIS-NDVI data, values are multiplied by 100 (left) and their corresponding spatial patterns (right).
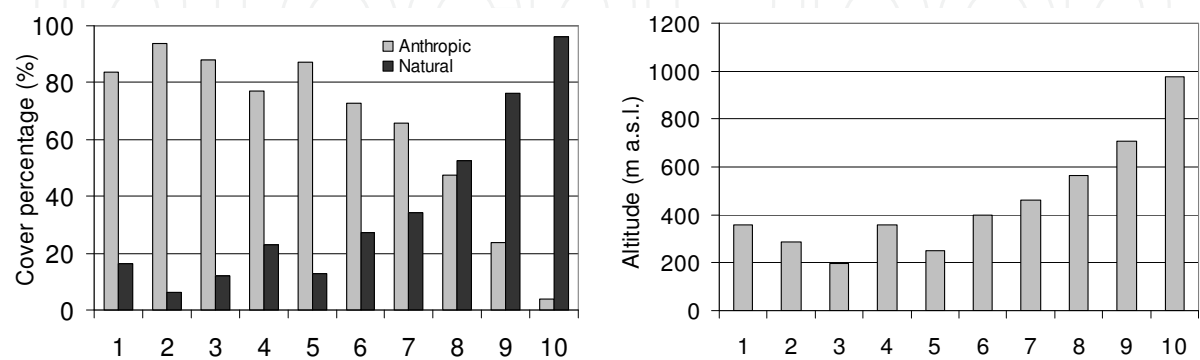
Fig. 4. Relative distribution of natural and anthropic covers (left); mean altitude value per phenological cluster (right). Shown data are related to 2005 as representative also of the other three years.

The distribution of the clusters along the altitude gradient starts from the central hilly areas of the first two clusters, goes downwards to the coastal aggregations, and then gradually increases from cluster 5 up to the mountainous areas of cluster 10. The only exception is represented by cluster 4 that is more spread over the territory being also composed by scrub and herbaceous vegetation associations for the natural portion (high presence of sclerophyllous vegetation, often left to delimit cultivation fields).

6.2 Spatial and temporal variability of vegetation patterns

The clustering analysis of the four investigated years does not highlight dramatic changes in the spatial aggregation of the phenological clusters (Fig. 5). The distribution of cluster cores seems to be very similar in the map sequence, particularly for the clusters with a high percentage of natural covers; whereas a slightly higher variability appears at the cluster borders.
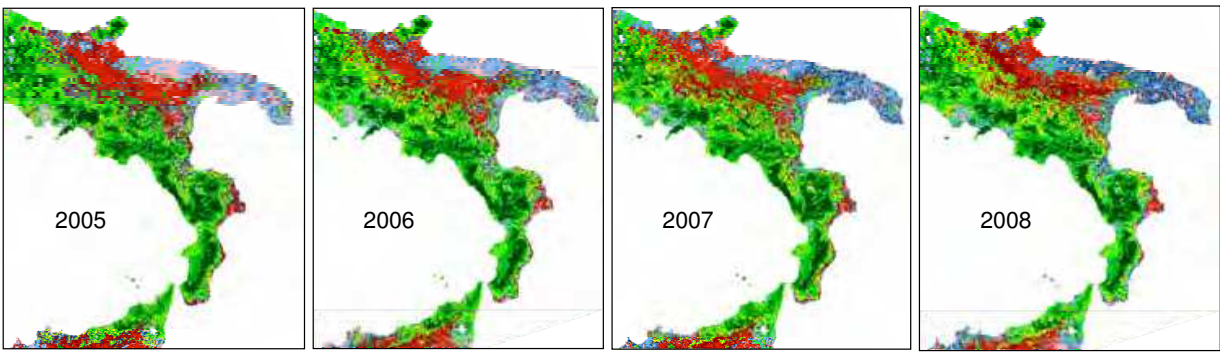
Fig. 5. Sequence of phenological maps obtained by the fuzzy classification.
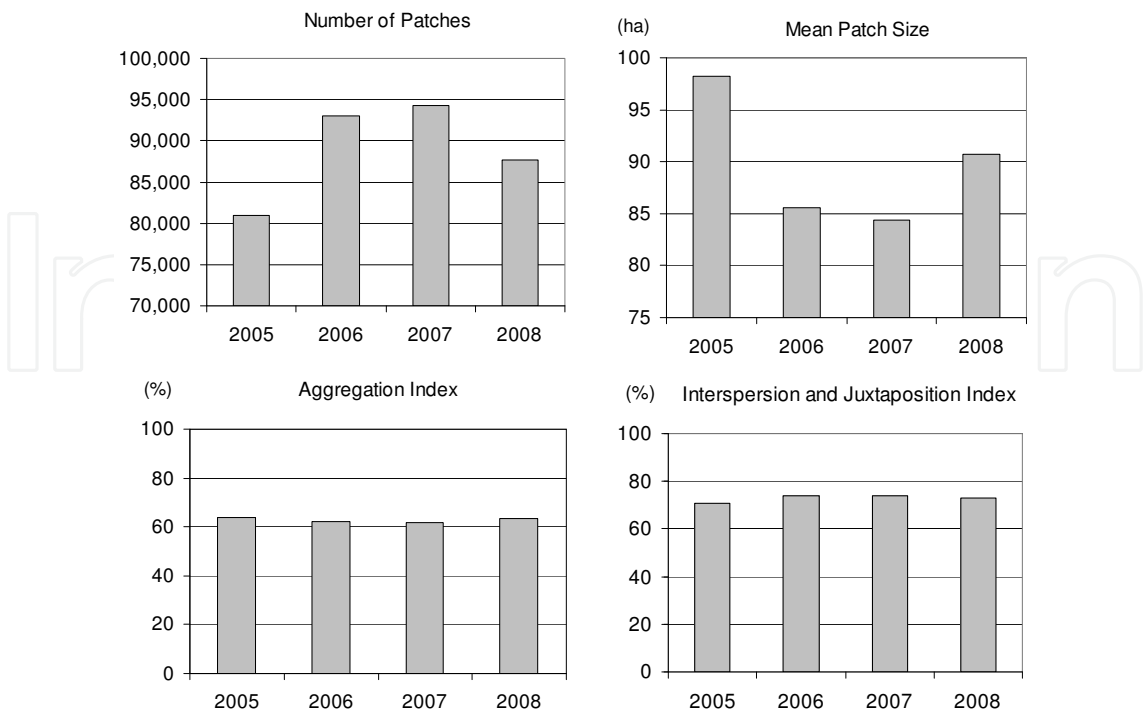
Fig. 6. Spatial characteristics of the phenological cluster aggregates.

To quantify the spatial variability of phenological aggregates, we analyzed the spatial structure of the maps (Fig. 6). Even if in 2006 and 2007 there is a higher number of patches (about 15%) having smaller dimensions, the level of cluster aggregation is quite high (~62%) and fairly constant. It was evaluated as the ratio between the number of like adjacencies (joins) inside the clusters and the greatest possible joins' number related to a maximally clumped shape with the same dimension of the given cluster. Similarly the level of interspersion and juxtaposing of patches belonging to different clusters is preserved in time. The Shannon's diversity index, commonly adopted in ecology to assess the richness of species (number and proportion), also shows quite high values (Fig. 7, top). In our case, being the cluster number constant, it highlights the level of uniformity in the proportional area distribution among the clusters.
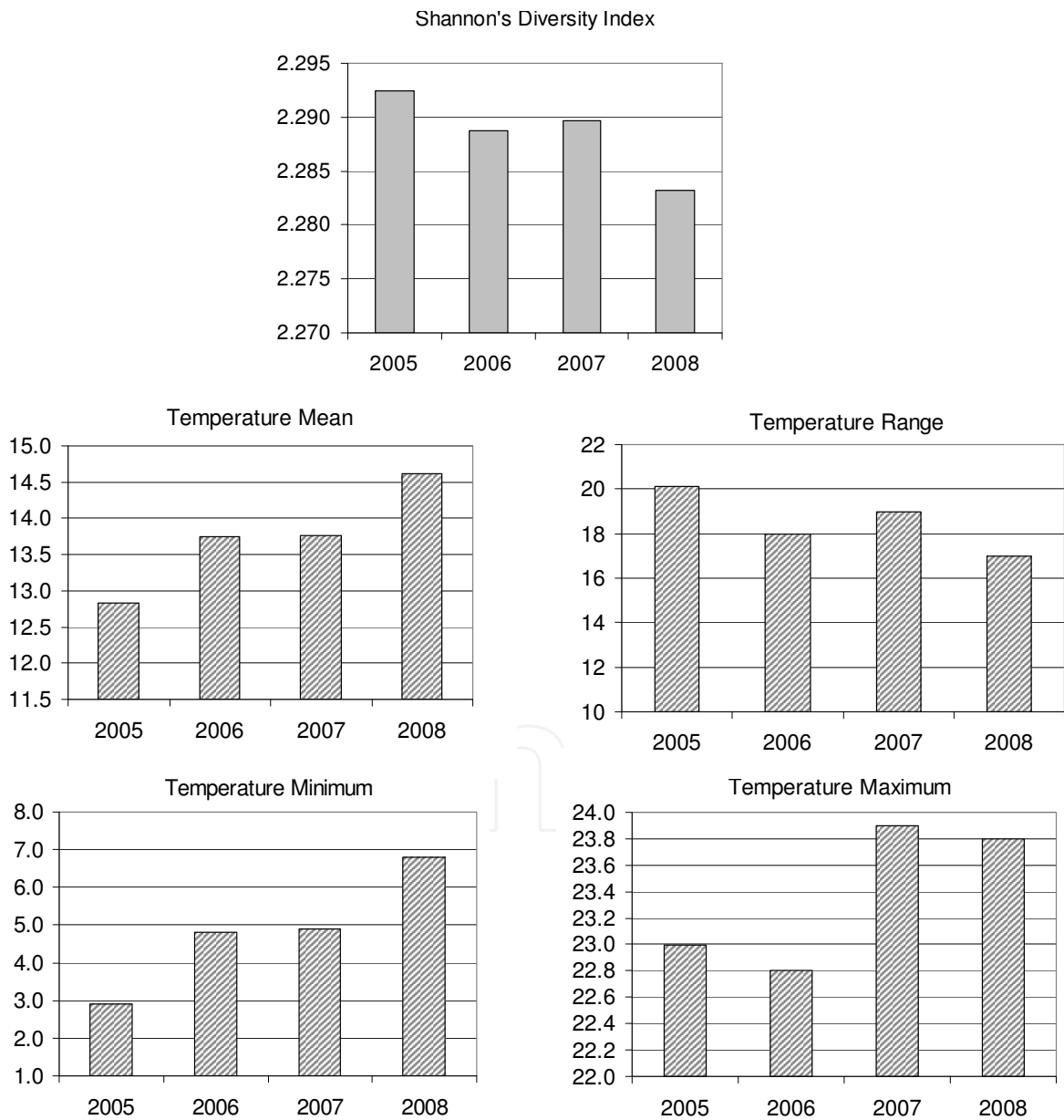
Fig. 7. Shannon's diversity index evaluated on the phenological maps (top) and characteristic parameters of mean temperature profiles for the whole study areas.

Among the four years, 2005 shows the most equitable cluster distribution; instead in 2008 the phenological aggregates appear to some extent less uniformly distributed. At broad scale level, such variation in the spatial heterogeneity evidenced by the Shannon's index appears to follow the behavior of temperature features (Fig. 7, bottom). In particular, it seems to be positively related to the annual temperature range (R 0.95) and negatively affected by the temperature mean and minimum values (R -0.97). The maximum of temperature does not appear to have a direct link with the spatial uniformity of phenological aggregates.

The NDVI profiles corresponding to the spatial clusters show a great variability, particularly in the growing and greening seasons with differences in both amplitude and length (Fig. 8). Such marked interannual differences in NDVI values jointly with the relative stability of the phenological aggregates suggest the effect of external forcing, such as the variability in temperature seasonality, capable to generate collective modifications of phenological responses.
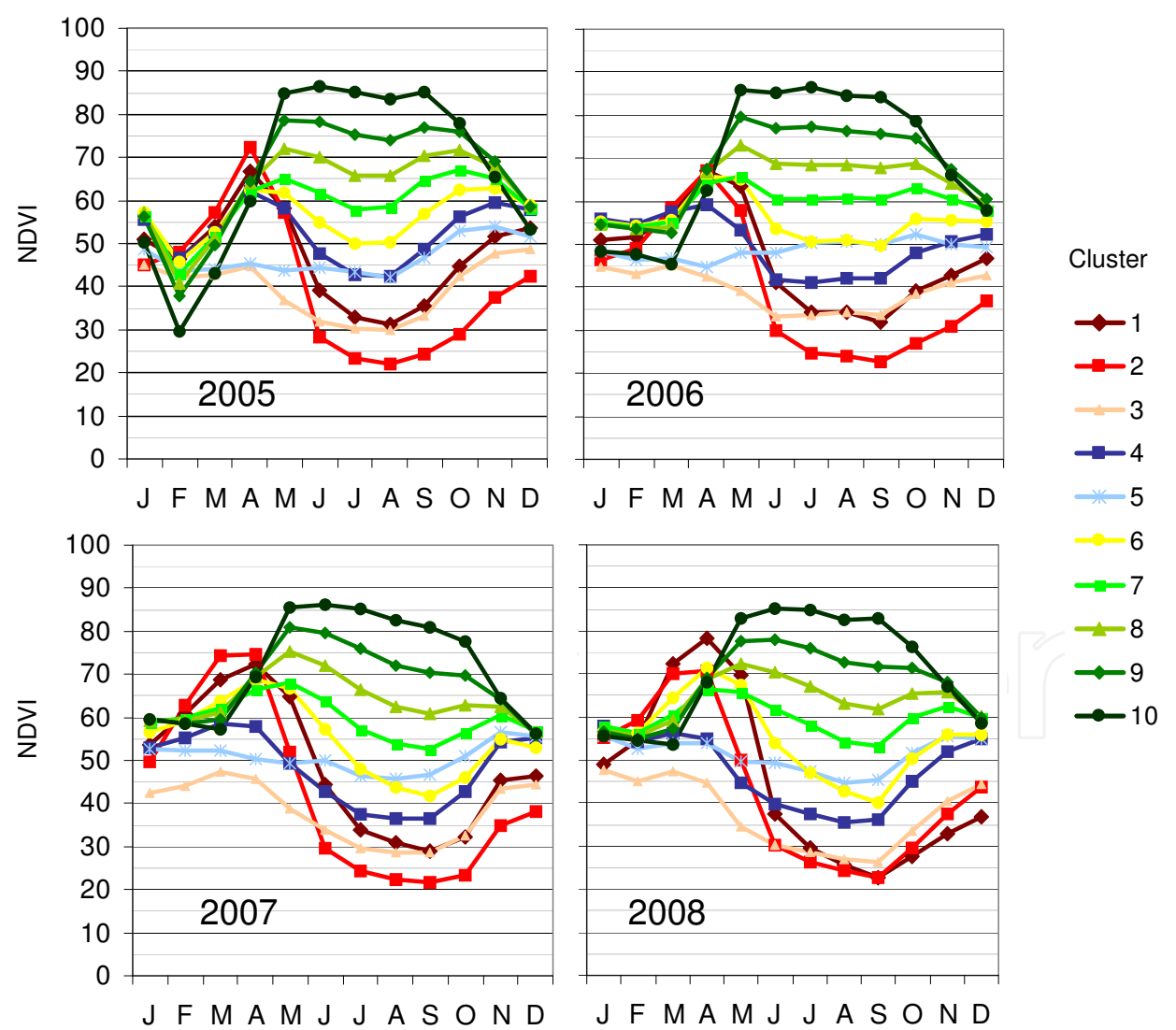
Fig. 8. Annual profiles corresponding to the phenological clusters in Fig. 8. The cluster colors in the maps correspond to the colors of the profiles.

The profiles of mean air temperature for the investigated area (Fig.9) seem to support such a hypothesis. In particular, 2005 appears colder than the other years during the first months to which low NDVI values correspond, especially in February. The relative low summer temperature in 2006, jointly with a gradual summer-autumn reduction, seems to characterize the flat behavior of vegetation response during the greening season of this year. The warmer initial period of 2007 and 2008 correspond to higher NDVI values during the first moths of both the years; conversely the warmer temperature in summer is related to a reduced vegetation activity response, except for the cluster at high altitude (cluster10). The behavior of the two years diverge from September, when 2007 show lower temperatures and slightly higher NDVI value reductions for the clusters with a large presence of natural covers.
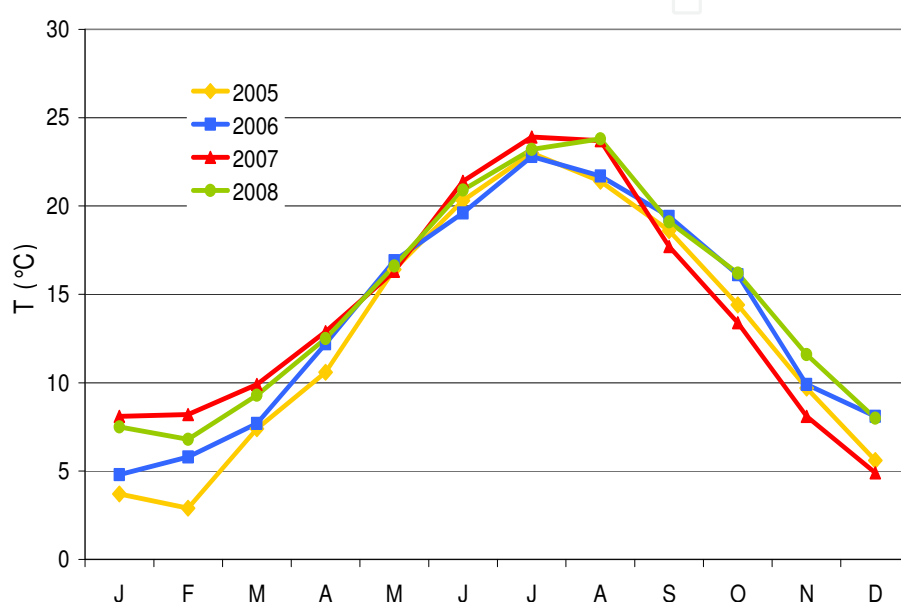
Fig. 9. Mean monthly temperature over the study area.

6.3 Correlation between vegetation and temperature patterns: r- maps

In order to investigate the relationship between temperature and vegetation development in detail, we analyzed the correlation between NDVI and T profiles at full spatial resolution by estimating the correlation per pixel (r-maps) (Fig.10).

The r-maps point out some leading spatial structures: there is a clear separation between the level areas of the Adriatic side (high negative correlation) and the Apennine areas of the Tyrrhenian side (high positive correlation). These aggregates are separated by a central transition area with low correlation magnitude.

The prevalent presence of cultivated lands in the level areas largely explains the anticorrelation in the phase-relation between phenology and temperature seasonality; whereas the high positive correlation on the Apennine mainly results from the diffuse presence of forested covers. In particular, broad-leaved forests and cultivations with olive and fruit trees represent the two extremes in the correlation range of the land cover classes: high positive the first and high negative the second (Fig. 11). The mixing and prevalence of peculiar covers determine the overall spatial structure of the correlation between vegetation

activity and temperature cycles. Where natural vegetation prevails, the correlation is positive and fairly high, where man managed covers are dominant, there is an opposite NDVI-T phase-relation and a reduced correlation magnitude. The spatial structure of correlation is then largely preserved in time: only small variations of the spatial patterns are present in the r-map sequence.
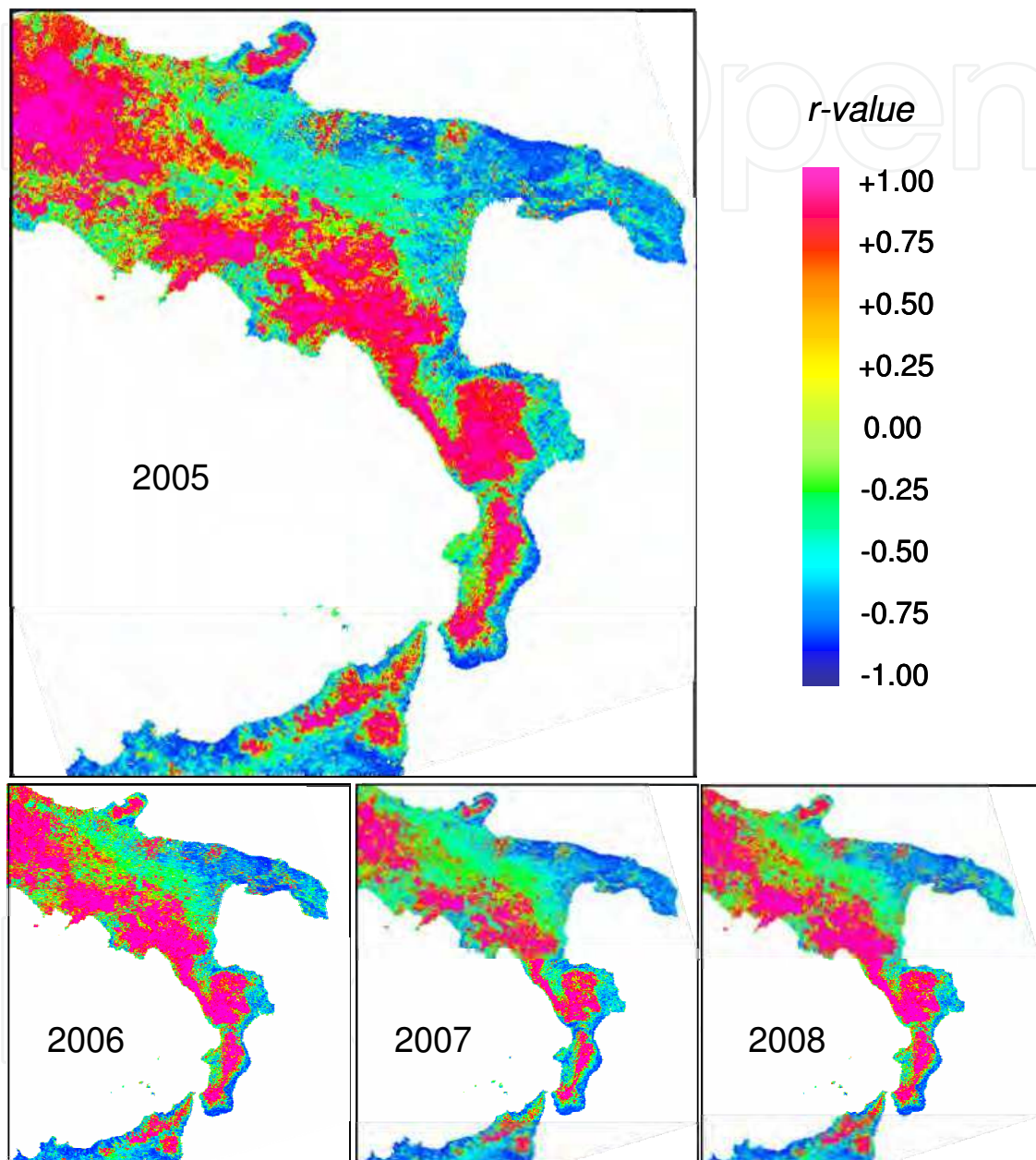

Fig. 10. Maps of correlation coefficient (r-map) between the NDVI and T seasonal profiles.

The strong link between land cover allocation and orography in the study area largely characterizes the distribution of correlation values along the altitude gradient (Fig. 12).

The correlation increases with the elevation and such a behaviour is preserved even if its strength is variable from one year to another. In particular, the variation in the correlation strength is higher in 2007 when there is a shift of the mean temperature profile, mainly

characterized by a warm initial period and colder autumnal-winter months (see Fig. 9). The different mean effects per altitude range (lower at high elevation) suggest different responses of the present vegetation to the peculiar 2007 temperature pattern.

Such different responses induced a large deviation toward anticorrelation in the distribution of vegetation-temperature phase-relation (Fig. 13), with a particularly evident population reduction for the highest correlation class in 2007.
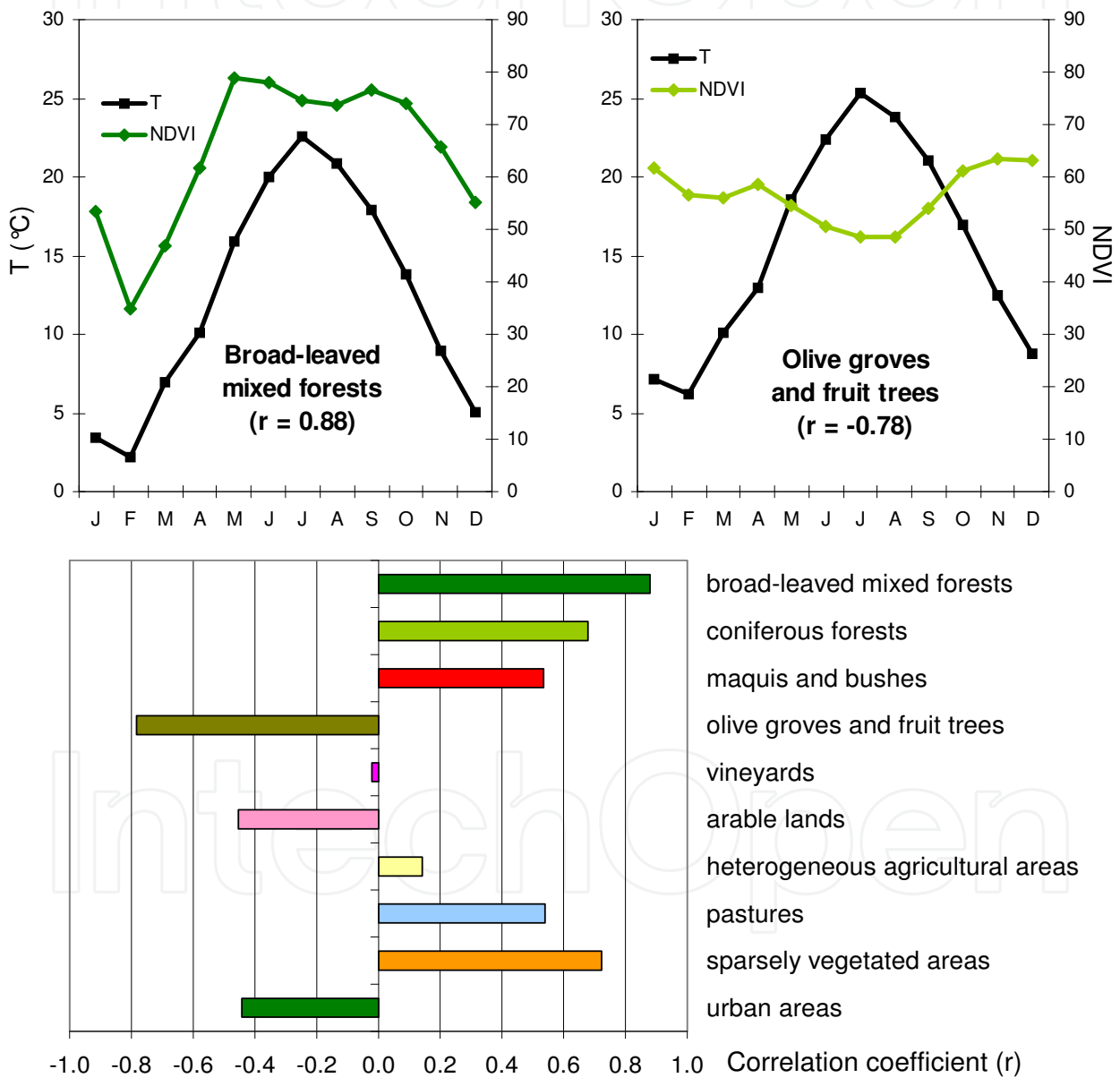

Fig. 11. Top: mean NDVI and temperature seasonal profiles for Broad leaved forests (high positive correlation) and Olive grove and fruit trees (high negative correlation); bottom: values of correlation between NDVI and temperature per land cover (data for 2005).
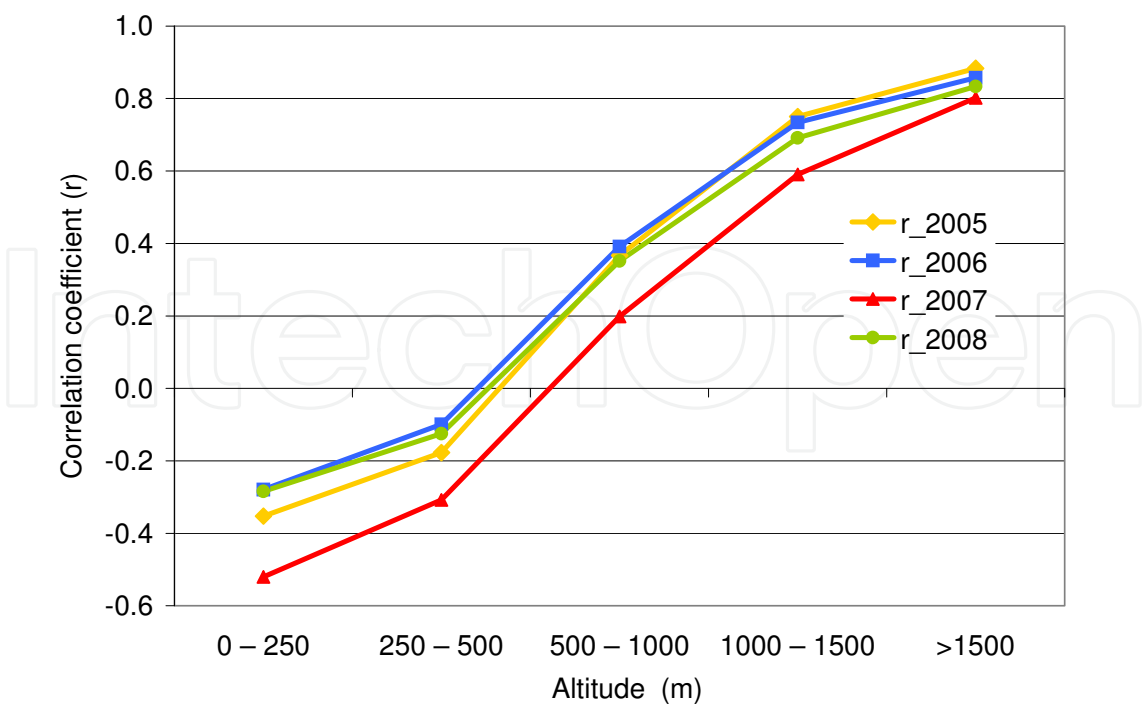
Fig. 12. NDVI and temperature correlation values per altitude range.
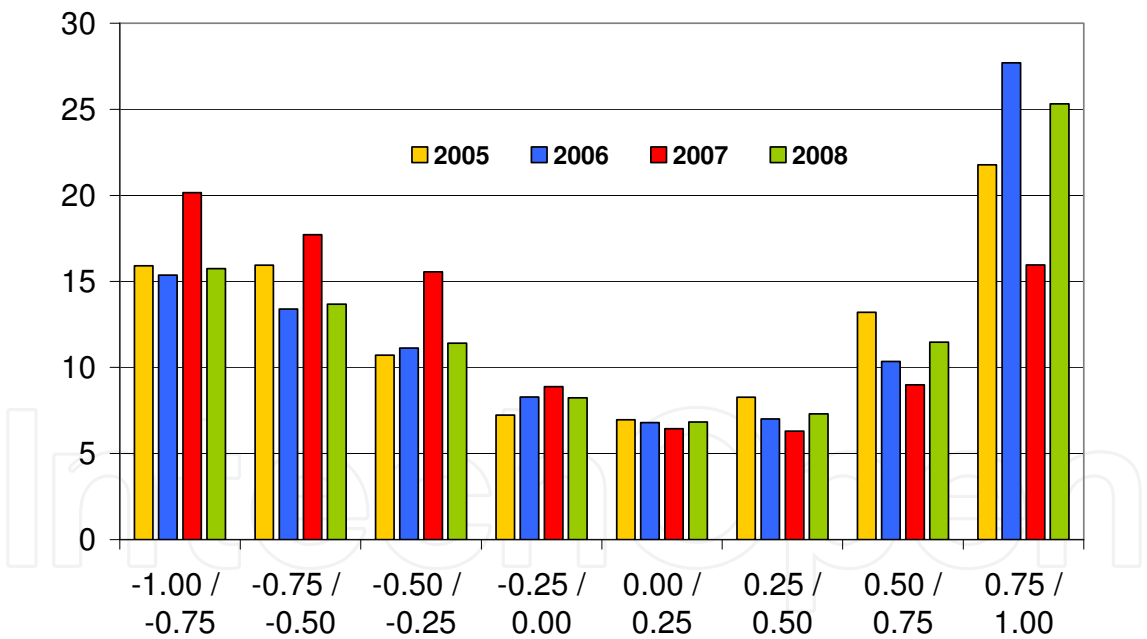
Fig. 13. Percentage distribution of correlation coefficients between NDVI and T profiles.

6.4 Spatial variability of phenological classes vs. temperature-vegetation temporal correlation

In order to evaluate the capability of the clustering procedure to follow the different responses of vegetation to temperature variability, we analyzed the changes in the cluster arrangements vs the correlation between phenology and temperature seasonality. We

compared the distribution of the correlation values for pixels that permanently belong to a given cluster during the investigated period (stable areas) with the distribution of pixels moving from one cluster to an other (unstable areas) (Fig. 14). For stable areas, even if there is some variability among correlation classes, the configuration of their distribution is preserved in time. For unstable areas, the shape of correlation distribution shows an evident modification in 2007.
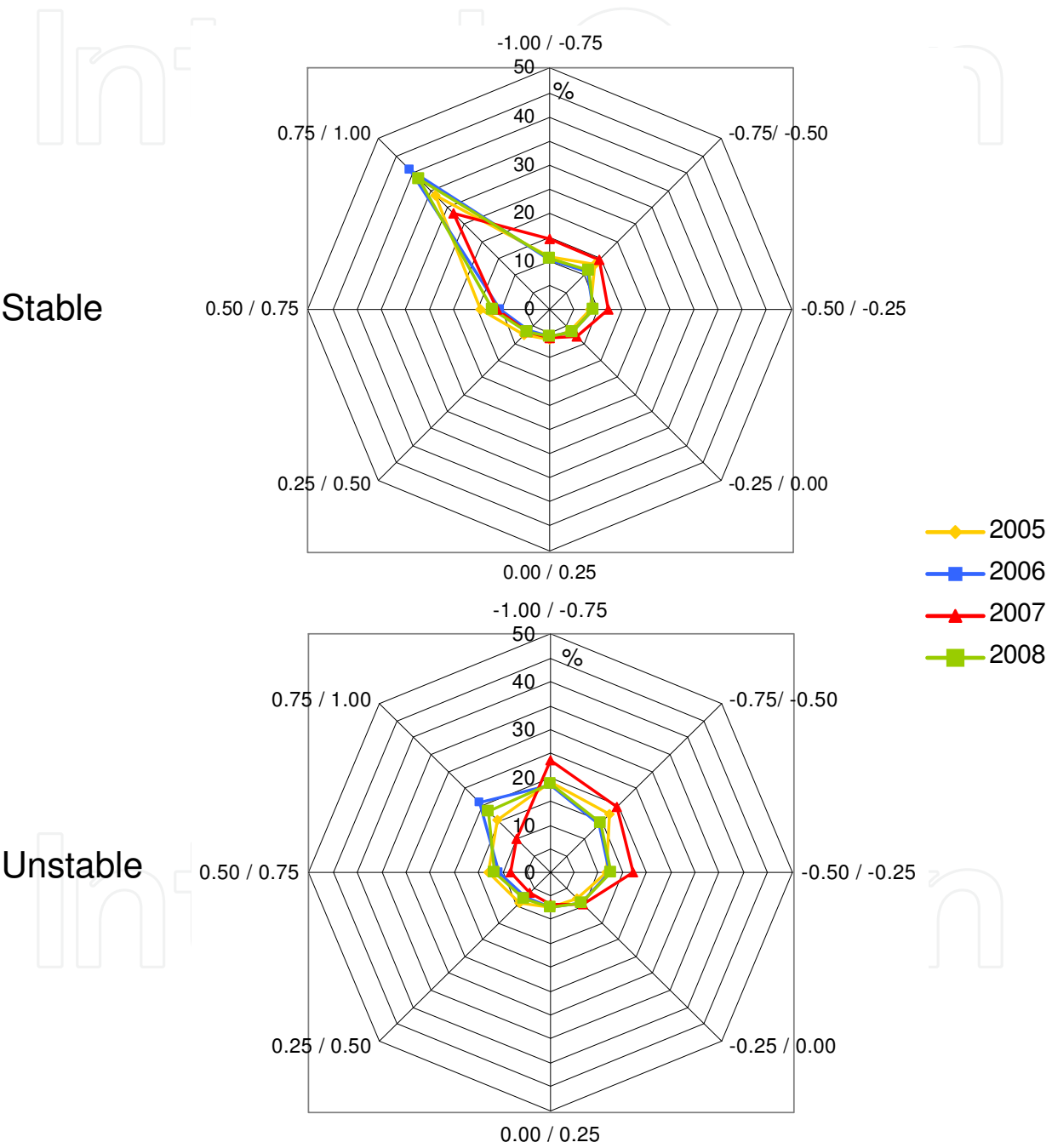
Fig. 14. Comparison of NDVI and T correlation value distributions for stable areas (persisting in the same cluster) and for unstable areas (changing clusters) for the whole investigated region. In the charts, the percentage distributions are represented in correlation bins between –1 and 1 at a 0.25 step.

To better analyze such different behaviours and to evaluate their relationship with temperature patterns, we focused on clusters with less anthropic influence. Then, we identified pixels moving from the cluster having the highest percentage of natural covers (cluster 10) during the investigated period. About 13% of pixels belonging to cluster 10 in
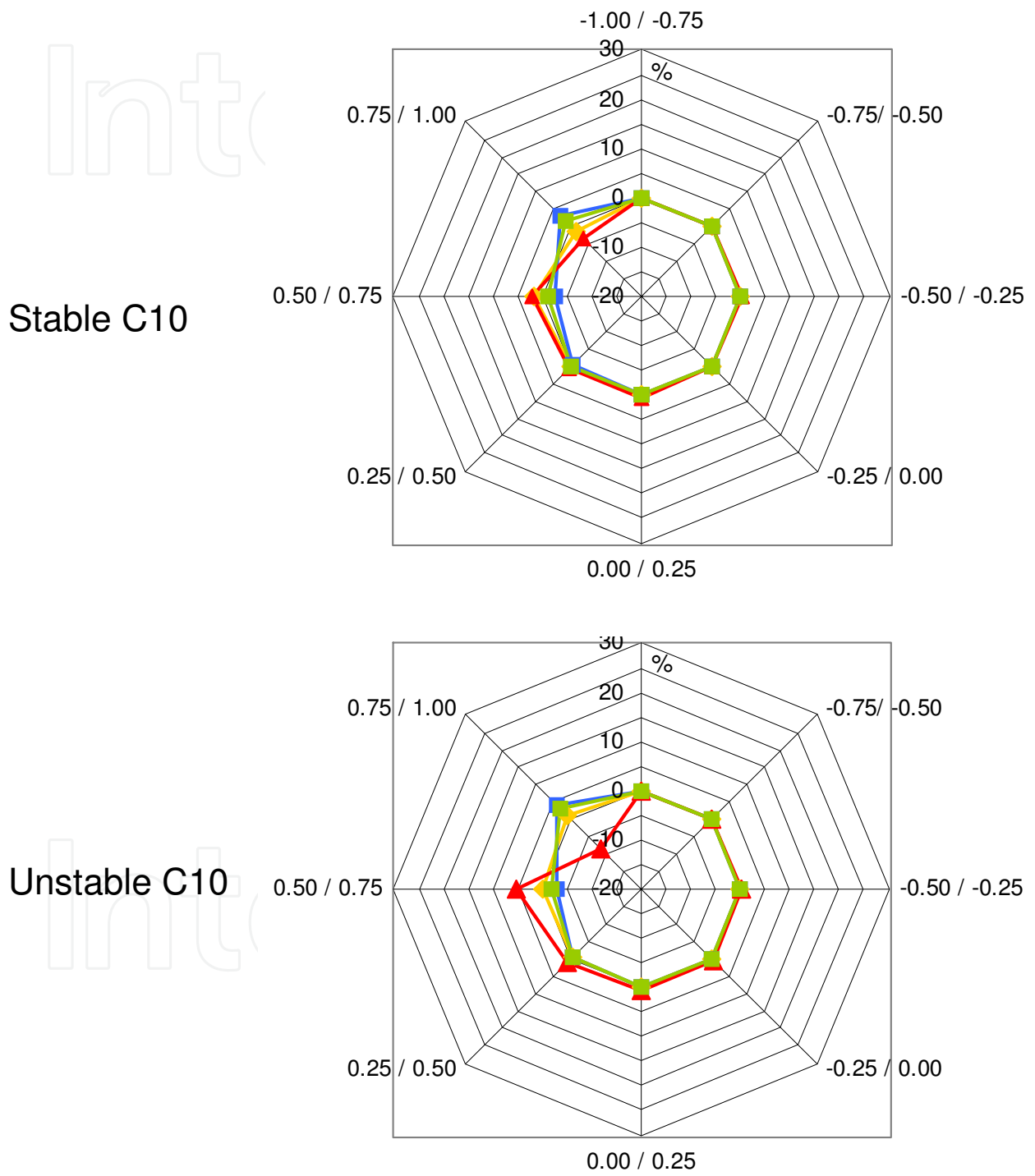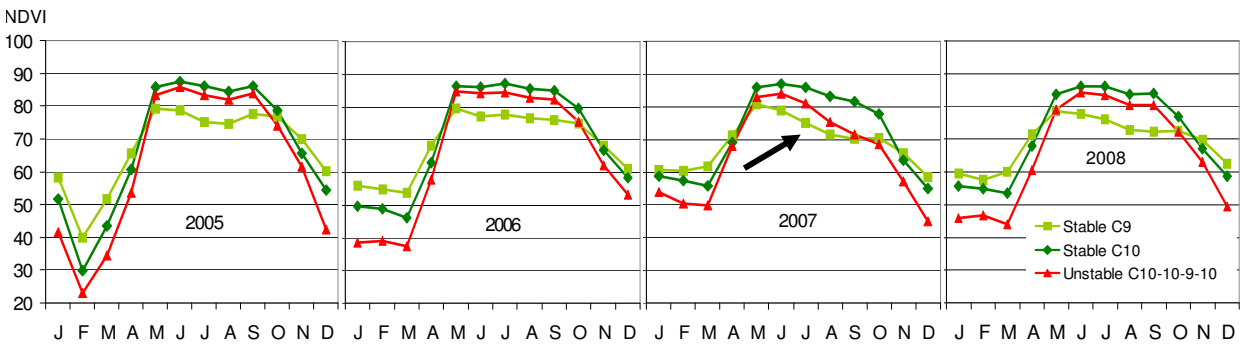

Fig. 15. Comparison of NDVI and T differences in correlation distribution for pixels stable in cluster 10 and for pixels transited to cluster 9 in 2007 (unstable C10). In the charts, the percentage distributions are represented in correlation bins between –1 and 1 at a 0.25 step.

Fig. 16. NDVI profiles for pixels stable in cluster 9 and cluster 10 and for pixels transited from cluster 10 to cluster 9 only in 2007.
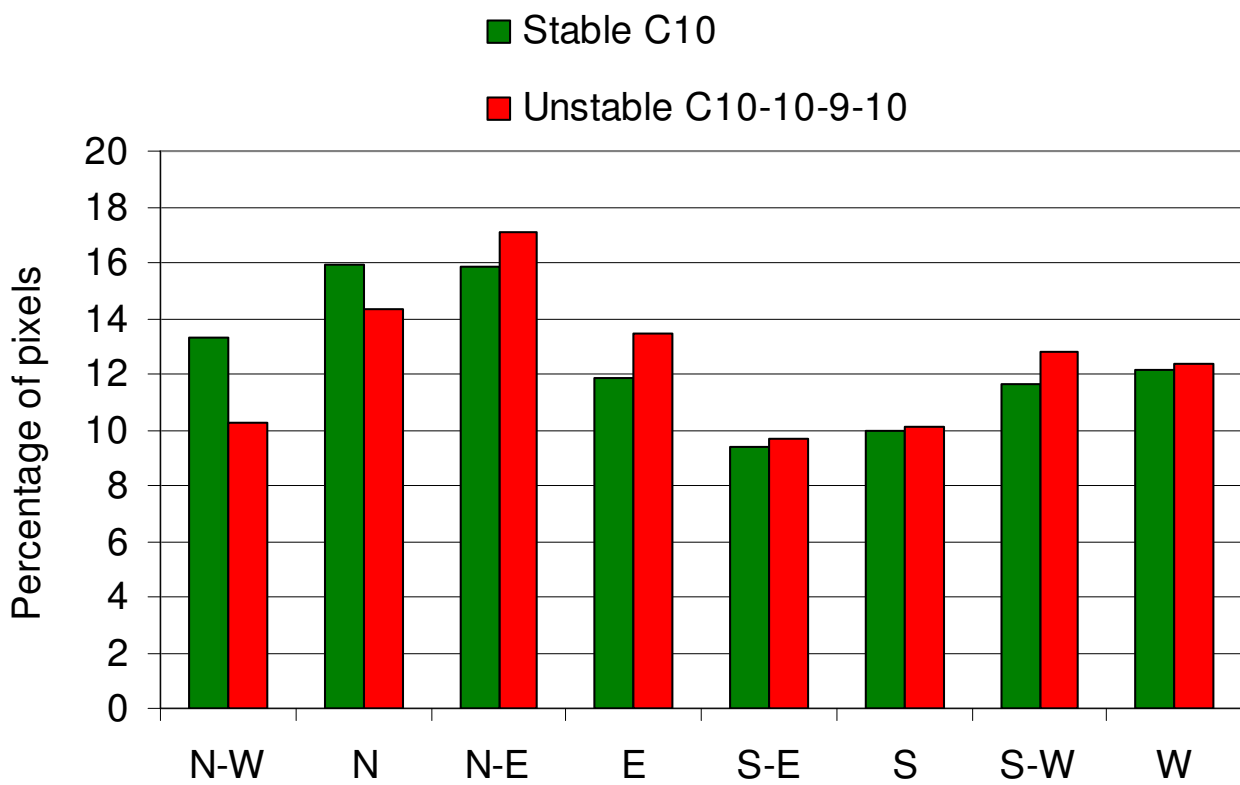

Fig. 17. Aspect distribution for pixels stable in cluster 10 and for pixels transited from cluster 10 to cluster 9 only in 2007.

2005, 2006 and 2008 were associated by the clustering procedure to cluster 9 in 2007. The quasi totality of such pixels is covered by forested areas (84%), mainly by broad-leaved trees, and is located at an average altitude around 1000m, similarly to stable pixels. By analyzing the differences in their distribution per correlation class (Fig. 15), we can note a marked configuration change in 2007. Conversely, pixels that are stable in cluster 10 during the four years considerably preserved the correlation distribution.

Such a variation in the correlation between vegetation and temperature cycles highlights a different phenological response of pixels transited to cluster 9 in 2007 compared to pixels persisting in cluster 10. As shown by NDVI cycles, the profiles of transited pixels, indeed, is very similar to those of cluster 10 in 2005, 2006 and 2008; whereas during 2007 it is more similar to the behaviour of cluster 9, in particular, in the summer period (Fig. 16). By analyzing the peculiarities of such transited pixels, we found a higher exposition to sunlight, mainly towards East – Northeast and Southwest, whereas stable pixels are prevalently exposed to North – Northwest (Fig. 17). The aspect factor could have exacerbated the effects of the warm summer and drought condition prolonged up to autumn in 2007.

7. Concluding remarks

Our results point out a significant degree of interannual variability of phenological responses, already evidenced by other studies (e.g. Hanes et al., 2010; Bradley et al. 2008), which interests not only herbaceous species but also structured vegetation, such as broad-leaved forests. The spatial distribution of phenological aggregates roughly reflects the macroscopic characteristics of the biogeographical variability (mainly altitude and land cover). Their spatial heterogeneity is characterized by a background structure, determined by the acclimatization setting, and by fluctuating components which aggregate to one or to another core according to different meteorological scenarios.

The joint evaluation of the cluster sequences and maps of correlation with temperature show that pixels persisting in the same clusters generally keep correlation even if both phenology and meteorology exhibit slightly different characteristic curves. Conversely, larger correlation differences are detected for pixels fluctuating among clusters, which could agree with the presence of non-linear phenology-temperature relationship (Hudson, 2010). This relationship is also influenced by some additional local features (e.g., surface aspect), whose effects emerge in mutated meteorological conditions. Since also rainfalls, jointly with the basic temperature variable, can have a relevant control in vegetation development especially in Mediterranean areas, future studies will be devoted to investigate the combined role of rainfalls in determining local phenological variability.

On the whole, the capability of the clustering procedure implemented on annual basis to follows the phenological modifications provides an indication for exploring the use of cluster spatial arrangement variations (dimension and shape) jointly with temperature-phenology correlation maps in studies devoted to model the vegetation responses to meteorological/climatic fluctuations also in the presence of non-linearity.

8. Acknowledgment

9. References

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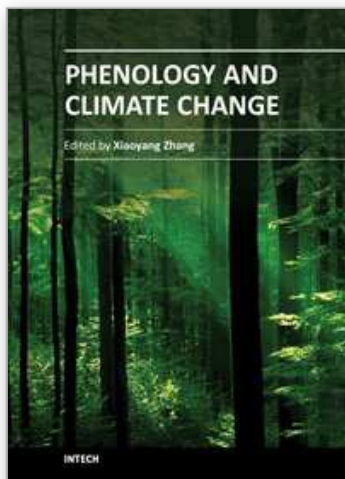
Phenology and Climate Change

Edited by Dr. Xiaoyang Zhang

Phenology, a study of animal and plant life cycle, is one of the most obvious and direct phenomena on our planet. The timing of phenological events provides vital information for climate change investigation, natural resource management, carbon sequence analysis, and crop and forest growth monitoring. This book summarizes recent progresses in the understanding of seasonal variation in animals and plants and its correlations to climate variables. With the contributions of phenological scientists worldwide, this book is subdivided into sixteen chapters and sorted in four parts: animal life cycle, plant seasonality, phenology in fruit plants, and remote sensing phenology. The chapters of this book offer a broad overview of phenology observations and climate impacts. Hopefully this book will stimulate further developments in relation to phenology monitoring, modeling and predicting.

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