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Disturbance patterns in a socio-ecological system at multiple scales

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ABSTRACT

Ecological systems with hierarchical organization and non-equilibrium dynamics require multiple-scale analyses to comprehend how a system is structured and to formulate hypotheses about regulatory mechanisms. Characteristic scales in real landscapes are determined by, or at least reflect, the spatial patterns and scales of constraining human interactions with the biophysical environment. If the patterns or scales of human actions change, then the constraints change, and the structure and dynamics of the entire socio-ecological system (SES) can change accordingly. Understanding biodiversity in a SES requires understanding how the actions of humans as a keystone species shape the environment across a range of scales. We address this problem by investigating the spatial patterns of human disturbances at multiple scales in a SES in southern Italy. We describe an operational framework to identify multi-scale profiles of short-term anthropogenic disturbances using a moving window algorithm to measure the amount and configuration of disturbance as detected by satellite imagery. Prevailing land uses were found to contribute in different ways to the disturbance gradient at multiple scales, as land uses resulted from other types of biophysical and social controls shaping the region. The resulting profiles were then interpreted with respect to defining critical support regions and scale-dependent models for the assessment and management of disturbances, and for indicating system fragility and resilience of socio-ecological systems in the region. The results suggest support regions and scale intervals where past disturbance has been most likely and clumped – i.e. where fragility is highest and resilience is lowest. We discuss the potential for planning and managing landscape disturbances with a predictable effect on ecological processes.

1. Introduction

Complexity arises inexorably when we generate descriptions or explanations of ecosystems that simultaneously consider multiple levels of organization or domains of scale (Allen and Starr, 1982). The complexity of ecological systems comprises inherent system properties like the multiplicity of spatial patterns and ecological processes, nonlinear interactions among components, heterogeneity in space and time, and hierarchical organization, but it also depends on the percep-

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tions, interests, and capabilities of the observer (Wu, 1999). Simon (1962) noted that complexity frequently takes the form of a hierarchy, whereby a complex system consists of interrelated subsystems that are in turn composed of their own subsystems. A hierarchy of ecological system levels can emerge during energy dissipation at different focal scales (O'Neill et al., 1986), and any ecological system, at a particular focal scale, appears constrained by the dynamics of larger scale systems (Allen and Starr, 1982). Each level is a domain of scale that can be visualized as a logical subsystem in a simulation model, and it is a region of scale-space where interactions among components have characteristic length and time scales.

The study of scaling is a way to simplify ecological complexity in order to understand the physical and biological mechanisms that regulate biodiversity (Brown et al., 2002). The very concept of biodiversity is inherently multiple-scale, with no preferred scale, and this (tautologically) demands multiple-scale study of the relevant features of the ecosystem. More pertinent is the observation that complex adaptive ecosystems such as the biosphere are self-organizing structures and patterns of interactions that arise from three simple rules (Levin, 1998): (1) sustained diversity and individuality of components; (2) localized interactions among those components, and; (3) an autonomous (self-contained) process that selects among components a subset for replication or enhancement. From these rules system properties emerge such as hierarchical organization and non-equilibrium dynamics (Levin, 1998) that require multiple-scale analysis, not only to comprehend how a system is structured but also to formulate hypotheses about mechanisms regulating the system (Milne, 1998).

The primary role of humans in shaping the environment implies that interpreting the sustainability of biodiversity in socio-ecological systems (SESs) in terms of resilience, adaptability, and transformability (Walker et al., 2004), must be related in some way to the environments that humans create. The terminology of sustainability implies an attractor or at least a basin of attraction (Walker et al., 2004), without which the concept of sustainability is irrelevant. Basins of attraction plausibly represent domains of scale (true attractors) within which interactions among components occur at characteristic length and time scales. According to the pattern – process hypothesis (e.g., Wu and Hobbs, 2002) these characteristic scales in real landscapes are determined by, or at least reflect, the spatial patterns and scales of human interactions with the environment. If the pattern or scale of human actions changes then the environment consequently changes, and the structure and dynamics of the SES can also change accordingly (Gunderson and Holling, 2002). Each SES is a complex system, and no SES can be understood by examining only one component, either social or natural, at one scale (Gunderson and Holling, 2002; Wu and Hobbs, 2002). Consequently, we cannot appropriately deal with a system property like "resilience" (Holling, 1973) unless we consider the entire SES. Displayed or retrospective resilience, as derived from the detection of past changes in the structure of the landscape, is fundamental to define the prospective resilience of a SES since the historical profile reveals a great deal about current system dynamics and how the system might respond to future external shocks (cf. Walker et al., 2002).

Ecological patterns and processes and human activities have interacted in SESs for a long time and are not just "coupled at a single scale." The human component is increasingly dominating in space and time (O'Neill and Kahn, 2000), thus defining limiting constraints at "higher scales" and altering the natural functioning of ecological processes in absence of human influences. Anthropogenic activities, such as agriculture, industry and urbanization, have radically transformed natural landscapes everywhere around the world, inevitably exerting profound effects on the structure and function of ecosystems (Millenium Ecosystem Assessment, 2003). The dynamic spatial configurations resulting from human appropriation and management of regional landscapes can have a variety of ecological effects within SESs over a wide range of spatial scales. A direct effect is the alteration of ecological processes at local scales through the modification of land cover. For example, converting forest to agriculture land cover alters soil biophysical and chemical properties and associated animal and microbial communities, and agricultural practices such as crop rotation alter the frequency of these disturbances. The spatial configurations of land cover in a region also affect ecological patterns and processes. New land cover types can be juxtaposed and shifted within increasingly fragmented remnant native land cover types, and changes in the structure of the landscape can have disturbing effects on nutrient transport and transformation (Peterjohn and Correll, 1984; Hobbs, 1993), species persistence and biodiversity (Aaviksoo, 1993; Fahrig and Merriam, 1994; Dale et al., 1994; With and Crist, 1995), and invasive species (Fox and Fox, 1986; With, 2004).

Though the term disturbance has been referred to natural causes (Pickett and White, 1985; Romme et al., 1998), here disturbances are relatively small and frequent changes (effects) in the structure of the landscape, as detected by remote sensing and mainly due to human activities (causes), that can reveal a great deal about how humans are affecting ecological patterns and processes.

In this paper, we address the problem of characterizing the spatial patterns of human-driven disturbances at multiple scales in a SES in southern Italy. This is an important first step towards understanding, in the context of complexity theory, how the actions of humans as a keystone species (O'Neill and Kahn, 2000) shape the environment and thereby biodiversity across a range of scales in this region.

The rapid progress made in generating synoptic multi-scale views and explanations of the earth's surface provide an outstanding potential to observe temporal changes in land use pattern as well as the scales of land use pattern (Simmons et al., 1992). Land use changes are signalled by a disturbance of the original land use. Thus, one way to appreciate the interactions between land use patterns and processes is to look at temporal changes in disturbance detected by remote sensing, and how they are associated with different land uses or regions of interest at multiple scales. If disturbance patterns and processes are modified in space and in time, then the adaptability of SESs (Walker et al., 2002), that is the capacity of humans to manage resilience, would change accordingly. That could allow fostering, intentionally, the adaptability of SESs.

Zurlini et al. (2004, 2006) suggested that different resilience levels in watersheds are intertwined with different scale domains according to the type and intensity of natural and human disturbances in those watersheds. In this work, we explore the multi-scale patterns of disturbances in an administrative unit (Apulia region) in relation to its land use composition. We hypothesize that differences in multi-scale patterns of disturbance are associated with land uses, because land uses result from other types of biophysical and social controls shaping the regions of interest. We describe an operational framework to identify multi-scale profiles of short-term anthropogenic disturbance patterns using a moving window algorithm to measure the amount and configuration of disturbance as detected by satellite imagery. The resulting profiles are then interpreted with respect to defining critical support regions and scale-dependent models for the assessment and management of disturbances. Results are also discussed in relation to their potential for indicating system fragility and resilience of socio-ecological systems.

2. Materials and Methods

2.1. *Study area and ecological response variable*

The Apulia is an administrative region in southern Italy (Fig. 1) that has been inhabited for thousands of years, so that man and nature have a long-lasting historical interrelationship. In recent centuries, anthropogenic pressure on Mediterranean ecosystems and abandonment of intense agricultural and pastoral practices has shaped plant communities into a mosaic-like pattern composed of different man-induced degradation and regeneration stages (Naveh and Liebermann, 1994).

Table 1 summarizes the land cover in the Apulia region as shown by the CORINE land cover map (CLC; Heymann et al., 1994) at a scale of 1:100,000 (Fig. 1) with a 25-ha minimum mapping unit. Overall, 82.4% of the region contains agro-ecosystems including arable land (39.8%), complex cultivation patterns and heterogeneous agricultural areas (13.4%), extensive olive groves (22.0%), and fruit tree orchards (7.2%). Major towns and small urban settlements account for only 3.8% of the entire region. Natural or preserved areas are relatively rare (8.5% of the region) and contain forests (mostly with *Quercus pubescens*, *Quercus ilex*), marshes, lagoons, sub-Mediterranean arid grasslands (*Brachypodio-Chrysopogonetea*), and coastal habitats of dunes, garigues, steppes and sub-Mediterranean maquis. There is substantial variation in land cover among provinces (administrative sub-units) in the Apulia region. The province-level proportion of urban area, for example, varies by plus or minus 100% from the overall regional proportion. The differences in type and intensity of land cover in different

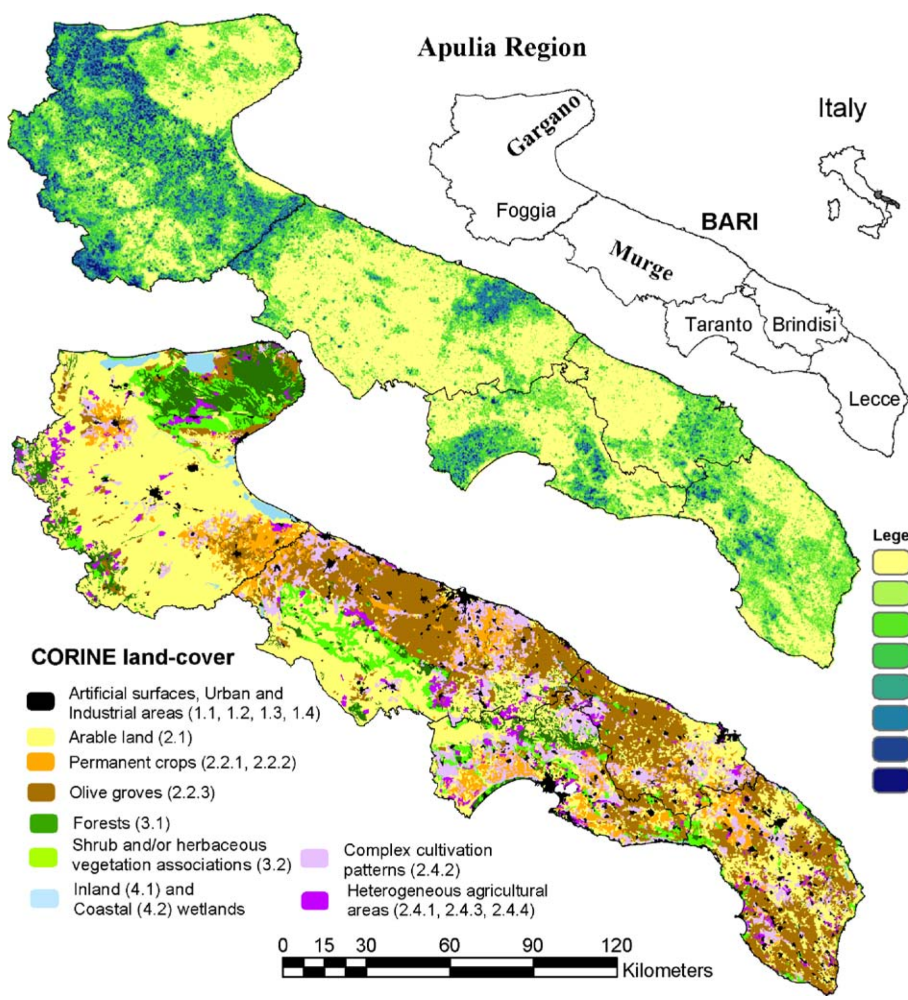

Fig. 1 – Simplified CORINE land cover map (at the bottom) of the Apulia region (South Italy) in 1999, and spatial representation of eight clusters (on top) relative to different multi-scale disturbance levels. CORINE codes are between brackets.

Table 1 – The CORINE land use and land cover composition of the Apulia region and its five provinces

Description	CORINE codes	Provinces (%)[a]					Region[a]	
		Bari	Brindisi	Lecce	Taranto	Foggia	ha	Percentage
Continuous urban fabric	1.2, 1.3, 1.1.1	2.9	3.3	5.7	4.1	1.43	56185	2.9
Discontinuous urban fabric	1.4, 1.1.2	1.2	0.8	1.1	1.7	0.28	16569	0.9
Arable land	2.1	29.5	26.9	32.1	27.4	57.97	758729	39.8
Olive groves	2.2.3	30.7	45.6	38.4	11.4	6.60	419676	22.0
Permanent crops	2.2.2, 2.2.1	7.8	5.4	5.7	13.1	5.80	137007	7.2
Pastures	2.3	0	0	0	0	0.03	194	0.01
Complex cultivation patterns	2.4.2	14.1	12.9	9.4	20.1	3.14	192056	10.1
Heterogeneous agricultural areas	2.4.1, 2.4.3, 2.4.4	2.8	2.4	3.0	4.9	3.41	62405	3.3
Forests	3.1	3.9	1.1	1.2	7.5	14.00	140689	7.4
Scrub and/or herbaceous vegetation associations	3.2	7.1	1.5	3.6	9.8	6.39	117101	6.1
Open spaces with little or no vegetation	3.3	0.01	0	0.06	0.05	0.96	7027	0.4

For each class percentages were calculated as related to the terrestrial surface of the administrative units (region or province) with the exclusion of inner water bodies and wetlands.

[a] Inland and coastal lagoons (CORINE code 4 and 5) were treated as missing values.

provinces make it more likely to observe spatial variation in disturbance patterns across the region. Large disturbances (Romme et al., 1998) from windstorms, floods, and fires are extremely rare in the region and did not occur within the temporal window of this study.

Six cloud-free Landsat Thematic Mapper 5 (TM) and two Enhanced Thematic Mapper Plus (ETM+) images were acquired and processed to describe the pattern of change for the entire Apulia region (Table 2). To capture mainly man-induced changes, we used a 4-year temporal window from June 1997 to June 2001. The normalized difference vegetation index (NDVI; Goward et al., 1991) was used as the ecological response variable. For this temporal window, NDVI changes can reflect small and frequent changes associated with farming practices such as crop rotation as well as the effects of drought, disease, fire, and urbanization.

The NDVI index is based on spectral reflectance in the red (R) and the near infrared (IR) channels:

$$\mathrm{NDVI} = \frac{\mathrm{IR} - \mathrm{R}}{\mathrm{IR} + \mathrm{R}}. \tag{1}$$

The NDVI index has been used in many studies of vegetation disturbance and dynamics because of its simplicity and close relationship to variables of ecological interest such as the health and stress conditions of vegetation cover (Guyot, 1989). In our study, differences of NDVI between two different times at the same location (both gains and losses) were considered as disturbances (Petraitis et al., 1989) in that they refer to any detectable change in land use or land cover which could modify water availability, nutrient transport and transformation, and affect species persistence and biodiversity by varying birth and death rates of organisms, either directly or indirectly through the variation of exposure to enemies, competitors, and the variation of resources like space.

For each image in the set, we performed the usual registration, calibration, and atmospheric corrections before calculating NDVI values for each pixel. Image registration was achieved using a first order polynomial function derived by a common set of ground control points and a base map of the region. The maximum root mean square error (RMS; Jensen, 1996) is on the order of 0.3 pixel. Raw Landsat data were converted to at-satellite reflectance using header coefficients prior to atmospheric correction with a dark subtract procedure (Chavez, 1988). The Landsat ETM+ NDVI image was transformed to values comparable to the Landsat TM NDVI images by using a linear transformation between images based on overlapping areas (the lowest R^2 was 0.97). Finally, all NDVI scenes were mosaicked, and areas of no interest (e.g., inland and costal wetlands, inland and marine waters, small islands) were masked. Pixels outside the administrative boundary of the Apulia region were also treated as missing values.

2.2. Change detection

Change detection is needed to produce a map of disturbance to be used as input to the analysis of the pattern of disturbance.

Table 2 – Characteristics of Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+) images used for the change detection of the Apulia region (Italy)

Path	Row	1997		2001	
		Date (dd-mm, hh:mm)	Elevation (degree)	Date (dd-mm, hh:mm)	Elevation (degree)
189	31	15-06, 9:10[a]	60.78	26-06, 9:21[a]	62.06
188	31	24-06, 9:04[a]	60.58	27-06, 9:24[b]	63.39
	32	24-06, 9:04[a]	61.02	27-06, 9:24[b]	63.99
187	32	17-06, 8:58[a]	61.22	28-06, 9:09[a]	62.46

[a] Landsat TM.

[b] Landsat ETM+.

Generally, change detection is based on the pixel-level differences in NDVI measurements from two co-registered images. In this study, we based the change detection on standardized differences $D(x, y)$ between two times (Zurlini et al., 2006):

$$D(x, y) = \frac{[f_{\tau 2}(x, y) - f_{\tau 1}(x, y)] - m}{\sqrt{s_{\tau 1}^2 + s_{\tau 2}^2 - 2cov_{\tau 1,\tau 2}}} \quad (2)$$

where $D(x, y)$ is the raster image of standardized change intensities indexed by the row (x) and column (y) of the map, $f_{\tau i}$ is the NDVI map at time τ_i, m is the mean of the pixel-level differences, $s_{\tau i}^2$ is the variance of the metric $f_{\tau i}$, and $cov_{\tau 1,\tau 2}$ is the covariance. Eq. (2) produces a map of change intensity deviations (NDVI gains and losses) from the mean intensity deviation, in standard deviation units.

Since the NDVI change index is a continuous variable, it is necessary to define a threshold of change; if the observed difference exceeds the threshold value, then the pixel is considered to be a ‘‘changed’’ or ‘‘disturbed’’ pixel. While threshold values are often set at one standard deviation (e.g., Fung and LeDrew, 1988), this choice is arbitrary since more or less of the map will be classified as ‘‘disturbed’’ if a different threshold is used. The statistical basis for choosing a threshold standard deviation is also questionable since the empirical distributions of $D(x, y)$ are usually leptokurtic and skewed. In this study, we set the threshold value corresponding to a fixed percentile (10%) of the empirical distribution of $D(x, y)$. This choice reduced the possibility of analyzing either the pattern of ‘‘background noise’’ that could be obtained with much higher (e.g., 40%) percentiles, or of emphasizing few local extreme values (e.g., 1% or less). The procedure also guaranteed that the analysis would include equal numbers of pixels of NDVI gain and loss. While any threshold is arbitrary, in our experience these choices capture 4-year changes of ecological significance due to transformations by human activities (Zurlini et al., 2006).

2.3. *Multi-scale patterns of disturbance*

Wu and Qi (2000) summarize the problem of incorporating scale in landscape pattern analysis. Of five theoretical components of pattern identified by Li and Reynolds (1994), the two most fundamental components are composition and configuration. Composition refers to the amounts of various entities in a landscape and configuration to their spatial arrangements. Observations of both are scale-dependent, and are intertwined such that one cannot study configuration independently of composition. A moving window algorithm is a powerful device for analyzing composition and configuration at multiple scales from satellite imagery. Each location in an ecosystem is characterized according to the amount and spatial arrangement of the entities within its surrounding landscape, for several landscape sizes. Large windows are more sensitive to low-frequency spatial patterns, and small windows to high-frequency patterns. Examples of applications of the algorithm in landscape ecology include fractal analysis (Milne, 1991), lacunarity analysis (Plotnik et al., 1993), edge detection (Fortin, 1994), spectral analysis (Keitt, 2000), fragmentation analysis (Riitters et al., 2000), and habitat representation (Dale et al., 2002).

We measured the amount of disturbance and its adjacency on the binary map (disturbed, undisturbed) that was produced by the change detection procedure. We used the moving window algorithm to place a set of 10 fixed-area windows around each pixel. The windows varied in size from 3 pixels $\times$ 3 pixels (0.81 ha) to 225 pixels $\times$ 225 pixels (4556 ha). Within each window, we measured the amount (area) and adjacency (connectivity or contagion; Riitters et al., 2000) of disturbance, and stored the results at the location of the subject pixel in the center of the window. The amount of disturbance was expressed as the proportion of disturbed pixels (Pd), and adjacency as the probability that a pixel adjacent to a disturbed pixel was also disturbed (Pdd; Fig. 2).

By repeating the measurements for every pixel over a range of window sizes, we quantified and mapped the amount and adjacency of disturbance as exhibited at various spatial frequencies over the study area.

For a given location, the trend in Pd with increasing window size can be interpreted with respect to the disturbances experienced by that location at different spatial lags. For example, a small window with high Pd combined with a large window with low Pd implies a local heavy disturbance embedded in a larger region of fewer disturbances. Locations characterized by constant Pd over window size experience equal amounts of disturbance at all spatial lags. For the entire population of locations, the trend tends asymptotically to the limiting values of Pd = 0.1 (i.e. to the threshold value of 10%), and Pdd = 0.414, which are, respectively, the overall proportion of disturbed pixels and the overall adjacency of disturbance (connectivity) of the entire Apulia region.

If trends are similar for two different locations, then both locations have experienced in their surrounding landscapes the same ‘‘disturbance profiles’’ as characterized by the amounts of disturbance at different spatial scales. Conversely, dissimilar trends imply differences in spatial profiles of disturbance. In principle, each location could have a unique disturbance profile, but in practice, we are interested in

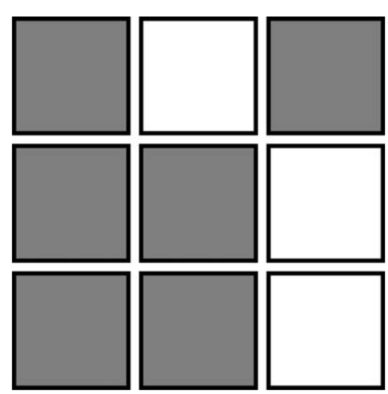

Fig. 2 – Example of the computation of Pd and Pdd for a landscape represented by a 3 $\times$ 3 grid of pixels, where disturbed pixels are shaded. In this example, six of the nine pixels are disturbed and so Pd equals 6/9 or 0.67. Considering pairs of pixels in cardinal directions, the total number of adjacent pixel pairs is 12, and of these, 11 pairs include at least one disturbed pixel. Five of those 11 pairs are disturbed-disturbed pairs, so Pdd equals 5/11 or 0.45 (modified after Riitters et al., 2000).

grouping locations according to the similarity of their profiles. Thus, we performed a cluster analysis, using the k-means algorithm (Legendre and Legendre, 1998), to group pixels according to the similarity of Pd values over all 10 window sizes. The k-means procedure identifies a pre-specified number of clusters by using an iterated centroid sorting algorithm to assign individual pixels to each cluster. Recognizing that any clustering solution is at least partly arbitrary, we specified that eight clusters be identified after experimenting with other alternatives.

Pd and Pdd metrics are naturally related to some degree because the configuration of disturbance is physically constrained by the amount of disturbance present in a window. As a result, there was not much difference between the clusters based on Pdd profiles in comparison to clusters based on Pd profiles. Instead, we incorporated information about the adjacency of disturbance (Pdd) after the clusters were identified based on Pd values alone. To accomplish this, we calculated the average Pdd value for all pixels contained within each cluster, for each window size. The Pd − Pdd metric space (Fig. 3) helps to interpret the physical meaning of the adjacency of disturbance for a given amount of disturbance (Riitters et al., 2000). For a fixed value of Pd, if Pdd > Pd, the disturbance can be said to be clumped (Fig. 3b and d) because the probability that a pixel next to a disturbed pixel is also disturbed is greater than the average probability of disturbance within the window. Conversely, when Pdd < Pd on a binary disturbance map, the implication is that whatever is undisturbed is clumped (Fig. 3a and c). The difference (Pd − Pdd) characterizes a gradient from disturbance clumping to undisturbed clumping. The interpretation of "clumping" depends also on the orthogonal gradient from low to high values of Pd that is more or less related to the size of the clumps.

Percolation theory (Stauffer, 1985) helps identify critical values of Pd. For a completely random disturbance distribution on an infinite grid of pixels, and evaluating adjacency in cardinal directions, the disturbance is guaranteed to occur in identifiable patches when Pd falls below a critical value of about 0.4. Below that value, the undisturbed pixels trace continuous paths across the window forming a general undisturbed matrix perforated by patches of disturbance (Fig. 3c). Conversely, as long as the disturbance is above a critical value of about 0.6, the disturbed pixels form such paths (Fig. 3a).

Not all the possible combinations of Pd with Pdd in Fig. 3 can occur. The more we approach the upper left corner or the lower right corner of the Pd − Pdd metric space, it becomes less likely to find disturbance patterns with very high Pd and very low Pdd, as well as with very low Pd and very high Pdd. Thus, all the possible expressions of disturbance pattern are more or less contained in an elliptic surface with the main axis given by Pd = Pdd. For a given amount of disturbance (e.g., Pd = 0.1), deviations from the main axis describe the pattern of disturbance Since the overall amount of disturbance in the Apulia region has been set relatively low (Pd = 0.1), attention is focused on the lower half of Fig. 3. In the lower left quadrant, typical disturbances occur as isolated pixels, whereas in the lower right quadrant, they tend to occur as clumps of pixels.

Our analysis is based on patterns of disturbed pixels as identified by the percentile of 10% for the distribution of the standardized difference of NDVI. The same approach could be used with different percentile values to explore the stability of clusters with respect to the definition of "disturbed area". If two comparable land cover maps were available, then the analysis could instead use change in land cover on a per pixel basis, which would enable disturbance to be defined as particular types of change such as "from grassland to urban".

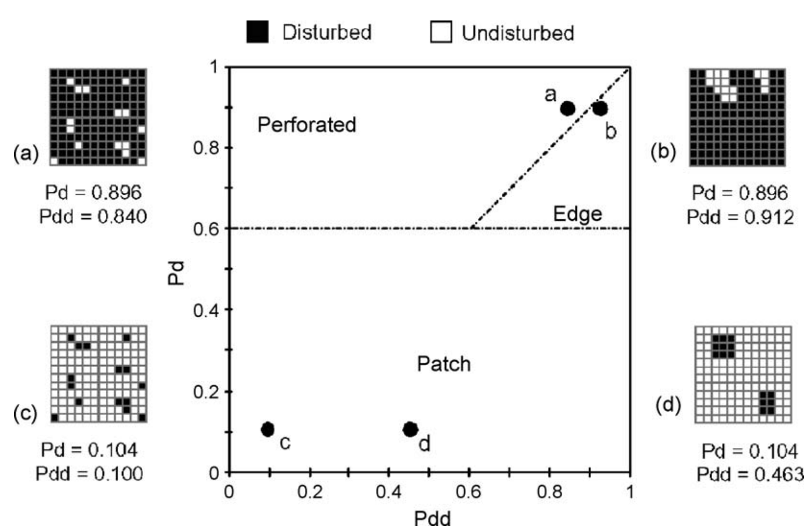

Fig. 3 – The graphical model used to identify disturbed fragmentation categories from local measurements of Pd and Pdd in a fixed-area window. Pd is the proportion of disturbed and Pdd is (roughly) the conditional probability that, given a disturbed pixel, its neighbor is also disturbed (modified after Riitters et al., 2000). Four simple examples of binary landscapes (a–d) are presented and located on the Pd − Pdd space for different combinations of composition and configuration: (a) highly disturbed but perforated by undisturbed areas (i.e. perforated disturbance), (b) highly disturbed but with clumped undisturbed areas (i.e. edge disturbance), (c) low level and highly fragmented disturbance, and (d) low level of clumped disturbance (i.e. patchy disturbance).

3. Results and discussion

Mean disturbance levels (Pd) for each window size for each of the eight clusters are shown in Fig. 4. Mean profiles of disturbance connectivity (Pdd) at multiple scales of the eight clusters are shown in Fig. 5, also as mean Pdd values for each window size. Cluster 1, which comprises 43% of the Apulia region (Table 3), contains the set of locations for which disturbance is quite low for all window sizes. Cluster 8, which comprises 2.5% of the region, corresponds to locations of actual disturbance; the mean Pd value approaches 1.0 in the smallest windows and decreases monotonically for larger windows.

The other six clusters, together comprising approximately 55% of the region, exhibit a variety of disturbance profiles whose shapes indicate the spatial scaling of disturbance. Cluster 3, for example, contains locations that are relatively undisturbed at local scale but are embedded in larger locations that have more disturbances. Cluster 5 includes locations that are relatively undisturbed at both local and larger scales, with more disturbances at intermediate scales.

The cluster map (Fig. 1) shows a geographic correlation of disturbance profiles. Cluster 1, for example, was common in the relatively less-populated Gargano National Park and the Murge, while cluster 8 tended to occur in the agricultural area of Foggia Province. At the same time, disturbance profiles are not determined by single land use Table 3 shows the percentages of different CORINE land uses associated with each cluster. If land use were the only factor determining disturbance profiles, then each land use would tend to appear in only a few clusters. Table 3 suggests that land use is not equally distributed across clusters, but there is no compelling evidence of a high correlation between land use and disturbance profile. The exceptions are olive groves, shrubs and grasslands, and urban fabrics which form most of clusters 1 and 2, and arable land which forms most of cluster 8.

Another way to evaluate this question is to compare the overall percentage of a given land use (Table 1) with the percentage in a given cluster (Table 3). If disturbances were distributed spatially at random, then the percentages should be almost the same. If the percentages are very different, then that land use makes a disproportionate contribution (more or less) to the cluster, and that would be evidence that the land use is responsible for the disturbance profile. A G-test of independence (Sokal and Rohlf, 1995) for the RxC frequency table of clusters and land uses (cf. Table 3) is found highly significant (d.f. = 63; $p < 0.01$) indicating that disturbances at multiple scales are not distributed randomly among land uses; some land uses contribute differently to the disturbance profiles from clusters 1 to 8.

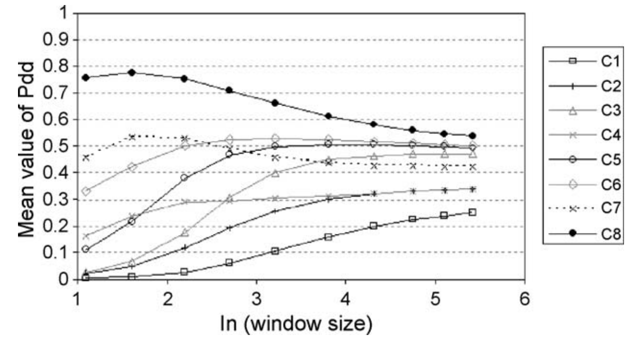

Fig. 5 – Pdd mean profiles (connectivity) at 10 different window sizes for the eight clusters identified in the Apulia region. Scale (i.e. window size) is in natural logarithms. Standard errors are not represented being very small due to the large number of pixels in each cluster.

Arable land, for example, comprises 40% of the total region (Table 1), but 78% of cluster 8. While cluster 8 is relatively uncommon in the region, it contains a disproportionate share of arable land, signifying that the highest disturbance levels in the region are attributable to land uses associated with arable land. Discontinuous and continuous urban fabrics comprise 3.2% of the total region, and are concentrated in the relatively undisturbed clusters 1 and 2. Olive groves comprise 22% of the total region (Table 1), but 35.4% of cluster 1, indicating that olive groves are among the least disturbed land uses. From this perspective, olive groves may be viewed as stabilizing the entire disturbance pattern regime of the Apulia region. Disturbance on arable land contributes to all clusters, but disturbances tend to be concentrated in about one-third of the entire region in the northern province of Foggia (Fig. 1).

Clusters 1 and 2, which together comprise 66% of the region (Table 3), have disturbance profiles indicating a relatively low degree (<10%) of disturbance for all window sizes. The disturbances that do occur in these clusters are widespread and isolated. Clusters 7 and 8 have large mean Pd values for small windows, implying the locations contained in those clusters are themselves disturbed, and for these clusters the decrease in mean Pd is quite rapid with increasing scale, also implying that the disturbances are widespread and isolated. The other clusters (3–6) representing approximately 30% of the study area comprise pixels that are not themselves disturbed, but occur more or less near disturbed pixels. It is within these clusters that the dominant regional trends are least likely to apply.

A plot of the cluster means in Pd − Pdd metric space (Fig. 6) helps to explore the spatial distribution of disturbances. Recall that the clusters were formed by using only the Pd values, and that to some extent, the values of Pd and Pdd are necessarily correlated within a window. If the correlation was the same across clusters, then the trajectories shown in Fig. 6 would be

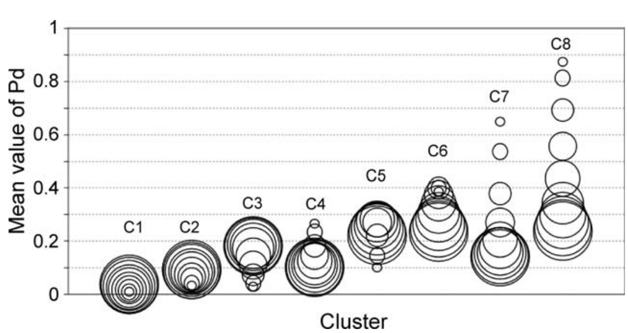

Fig. 4 – Cluster means of the disturbance density metric (Pd) for the eight clusters at 10 different window sizes identified through the k-means clustering of the map of change for the entire Apulia region.

Table 3 – Cluster percentage importance and land cover composition as derived by the CORINE land cover data base for the eight clusters identified in the Apulia region

Description	CORINE codes	Cluster (percentage)							
		C1	C2	C3	C4	C5	C6	C7	C8
Continuous urban fabric	1.2, 1.3, 1.1.1	3.21	4.71	1.73	2.40	0.38	0.23	0.59	0.28
Discontinuous urban fabric	1.4, 1.1.2	1.01	1.29	0.35	0.95	0.08	0.04	0.25	0.03
Arable land	2.1	31.40	37.95	53.21	35.44	55.55	58.53	50.94	78.16
Olive groves	2.2.3	35.44	19.12	7.36	14.28	2.96	2.33	7.29	1.60
Permanent crops	2.2.2, 2.2.1	0.70	5.63	13.88	13.19	22.85	22.76	17.89	10.22
Pastures	2.3	0	0	0.02	0.01	0.04	0.08	0.03	0.04
Complex cultivation patterns	2.4.2	7.39	13.27	11.94	15.81	8.87	7.52	11.81	3.20
Heterogeneous agricultural areas	2.4.1, 2.4.3, 2.4.4	2.98	3.84	3.00	4.23	3.08	3.15	3.13	1.95
Forests	3.1	8.01	8.45	5.87	8.57	4.76	3.97	5.25	2.98
Scrub and/or herbaceous vegetation associations	3.2, 3.3	9.87	5.75	2.65	5.12	1.42	1.30	2.82	1.55
Percentage of cluster on total area		42.84	23.06	10.65	8.34	5.76	3.56	3.28	2.50

superimposed on each other as they described the overall regional trend of Pd with increasing window size. Clusters 1 (least disturbed) and 8 (most disturbed) do in fact seem to trace a single curve in Pd – Pdd space, perhaps along the lower boundary of an ellipsoid. We tentatively call this the lower 'baseline' curve for the relationship between Pd and Pdd in the region, above which all possible configurations of the systems considered can take place, and anticipate that the trajectories for all clusters must converge at the trivial value of Pd = 0.1 (the threshold percentile), and, less trivially, at Pdd = 0.414. With that in mind we can examine how the trajectories for the other clusters depart from that baseline.

Clusters 2, 3, and 5 are above and roughly parallel to the baseline curve. These are clusters for which the disturbance profile tended to increase with window size (Fig. 6). In contrast, clusters 4, 6, and 7, for which the disturbance profiles tended to decrease with window size (Fig. 6) are also above the baseline curve but are not parallel to it. In contrast to clusters 2, 3, and 5 for which the trajectory has Pdd always increasing with window size, the trajectory for these three clusters at first has Pdd increasing with window size, but then decreasing as the trajectory approaches the baseline curve. An increasing Pd with window size is expected to be associated with increasing Pdd (Fig. 6).

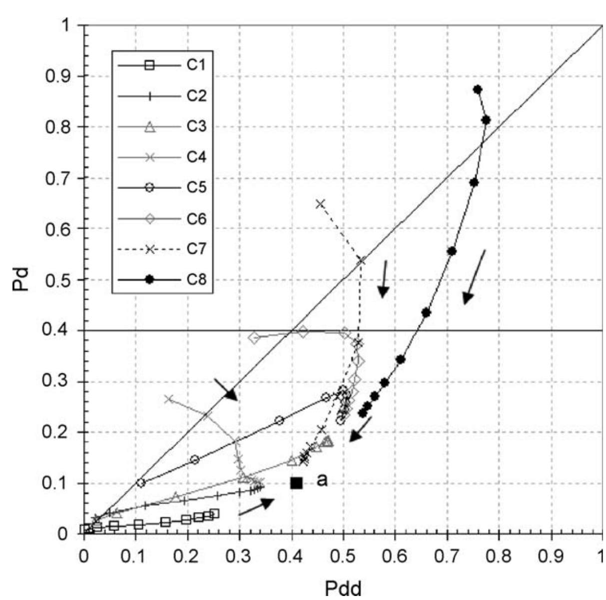

Fig. 6 – Multiple scales trajectories of the eight cluster means identified in the Apulia region. Arrows indicate the direction of cluster displacement from the finest (lower resolution limit) to the coarsest scale (upper limit of extent). All trajectories converge into a single point (a, upper limit of the study, extent) given by the overall Pd and Pdd at the entire region level. This seems a natural way to look at multi-scale patterns of disturbance.

4. Concluding remarks

There is an increasing need to identify and quantify natural and man-induced ecological changes and their corresponding patterns at multiple spatial scales, in order to help planning and management of landscape mosaics (Tischendorf, 2001). Measuring disturbance density and connectivity via moving windows is a way to approach landscape complexity to investigate causes, processes and possible consequences of land use and decision making at various scales. We could analyze and compare patterns of disturbance density and connectivity at multiple scales for different regions of interest in relation to certain driving forces at work as revealed by land use and land cover.

Classical land cover mapping would ignore apparent disturbances from crop rotation because agricultural fields, can be fallow one year and planted the next, and still be labeled as "agricultural fields." In our analysis, crop rotation is considered to be a disturbance, which is justifiable in the context of complexity analysis where such changes clearly demonstrate that agricultural fields are more dynamic than other types of land-use systems.

Disturbance density and connectivity through the Pd and Pdd metrics can be useful to provide support for landscape assessment of retrospective fragility and monitoring for risk. In this respect, a key complementary aspect of resilience is resistance (Carpenter et al., 2001) that refers to the amount of the external pressure needed to displace a system by a given amount. When external pressures affect intrinsic factors of resistance of the system, they might determine detectable changes which can be related to displayed fragility (cf. Nilsson and Grelsson, 1995). Changes (disturbance intensities) detected are just real transformations observed in a specific time lag, but they do not allow distinguishing between external pressure and resistance factors, as changes represent the result of their interaction. The type, magnitude, length, timing, and spatial configuration of pressure/disturbance, its predictability, the exposure of the system, and the system's inherent resistance, have important interactive relationships which determine the propensity of the system to displace from its stability domain to another domain. Such propensity can be named vulnerability or fragility, which appears inversely related to resilience (Gunderson and Holling, 2002; Zurlini et al., 2003, 2006).

If the same external pressure is applied to two systems with different intrinsic resistances, they will show a different resilience to resist lasting change caused by external pressures. In particular, we could simply think that the amount of external pressure (ν) coupled with intrinsic resistance (ρ) of a land use determines its resilience. In other words, resilience can be deemed as proportional to the resistance per unit of external pressure, i.e. ρ/ν (Zurlini et al., 2006), and both fragility and resilience can change spatially according to differences in pressures and resistances. If we might assume that a specific system can maintain the same intrinsic resistance independently of the possible configurations, its fragility can be simply indicated by both disturbance density (Pd) and connectivity (Pdd), and retrospective resilience by both 1/Pd and 1/Pdd in the Pd – Pdd metric space. Estimates of retrospective resilience can reveal a great deal about current system dynamics and, prospectively how the system might respond to future external shocks (cf. Walker et al., 2002).

Thus, going back to Fig. 6, one can think of the Pd – Pdd metric space as a state space where systems can trace multiscale paths and be ordinated according to their fragility-resilience. In that space the same type of system can exist and be identified in a collection of multiple self-organized and alternate states with particular trajectories across multiple scales. The limiting values of Pd = 0.1 for the extent region depends on the threshold value for change, so that point will shift upwards if one increases the 10% threshold, but in doing so it will increase also the risk of considering disturbance that is just background noise. As to Pdd, the system can shift leftwards or rightwards based on grain size; so, at the same amount of disturbance for a finer grain size clumping (Pdd) will be reduced, conversely at a coarser grain size clumping will be increased and system paths will occupy left hand sectors of the Pd – Pdd metric space. Undisturbed pixels form a general undisturbed matrix perforated by patch disturbances below the critical Pd value of about 0.4. Conversely, the disturbed pixels form such paths above the critical value of about 0.6. At the same Pd value, the difference (Pd – Pdd) characterizes a gradient from disturbance clumping to undisturbed clumping, and the interpretation of "clumping" depends also on the orthogonal gradient from low to high values of Pd that is related to the size of the clumps. Those gradients can be interpreted in terms of fragility-resilience gradients with fragility increasing with both Pd and Pdd from the lower left corner to the upper right corner in Fig. 6, whereas retrospective resilience has the opposite behavior. The trajectories of clusters can now be compared, and the most disturbed regions like clusters 8, 7 and 6 appear more fragile and less resilient at finer than at higher scales, and with respect to less disturbed regions like clusters 1, 2 and 3.

The social component of SESs consists of groups of people organized at multiple levels with differing views as to whether some system states are desirable and others undesirable. To prevent the system, or part of the system (scale intervals) from moving across the Pd – Pdd space to undesired system configurations, we have to identify the possible ways of reducing undesirable displacements of the system in response to a given amount of external pressure. Fragility and resilience can be modified either by stabilizing the ecological system, reducing external pressures or acting on pressure and resistance spatial patterns, and/or by modifying key ecological processes such as trophic relationships, eutrophication, and functional diversity. Results from this work provided indications to find support regions and scale intervals where disturbance has been most likely and clumped – i.e. fragility highest and resilience lowest, as retrospectively observed by past exposure to external pressures.

To increase landscape adaptability we have to look for actions that will go in the direction of restoring lost resilience, or enhancing it to allow a wider spectrum of suitable land use options. This could be achieved by (1) strengthening the socio-ecological feedbacks that tend to maintain a particular desired configuration of the system, and (2) foster and maintain the adaptive capacity of SESs which resides in aspects like memory, creativity, innovation, flexibility, and diversity of ecological components and human capabilities (Walker et al., 2002). Simulations techniques addressing disturbance pattern at multiple scales can help provide scenarios of disturbance density and connectivity, as a decision support system for evaluation, assessment and planning to address adaptive management of disturbance patterns by identifying sets of sustainable options.

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