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RESEARCH ARTICLE

Patterns of disturbance at multiple scales in real and simulated landscapes

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Abstract We describe a framework to characterize and interpret the spatial patterns of disturbances at multiple scales in socio-ecological systems. Domains of scale are defined in pattern metric space and mapped in geographic space, which can help to understand how anthropogenic disturbances might impact biodiversity through habitat modification. The approach identifies typical disturbance 'profiles' based on the similarity of trajectories in a pattern metric space over a range of spatial scales. When different profiles are coherent in pattern metric space, they describe a regional spatial pattern. The divergence of a profile indicates a scale-dependent transition to a local spatial pattern, which can be examined for correspondence to different regions of geographic space. We illustrate the conceptual model with simulated maps and real disturbance maps from satellite imagery in south Italy. The results suggest that management of disturbances in the study region depend less on local drivers of disturbance and more on broader-scale drivers within the socio-ecological framework.

Keywords Disturbance pattern · Neutral model · Moving window · Land use change

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Introduction

A major focus of landscape biodiversity research has been the investigation of species' responses to habitat area and fragmentation (Gardner et al. 1993; With and Crist 1995; Burke and Nol 2000; Boulinier et al. 2001). Human-caused habitat fragmentation is a landscape-level disturbance (Hobbs and Huenneke 1992) that precipitates biodiversity decline by excluding species and disrupting community interactions. To manage disturbance impacts on biodiversity, it is necessary to know how humans as a keystone species (sensu O'Neill and Kahn 2000) shape the environment across a range of scales in a region. Biophysical factors determine habitat potential, but within those constraints, human uses of the land ultimately determine habitat quantity and quality in specific places.

The concept of a complex socio-ecological system (SES) (Walker et al. 2002) takes into account the scales and patterns of human land uses as ecosystem disturbances. In the panarchy

(Gunderson and Holling 2002) of a socio-ecological landscape, the scales and patterns of habitat disturbance are the direct result of human interactions with the biophysical environment. Anthropogenic disturbances are imposed by groups of people who are organized at different levels (e.g., household, village, county, province, region, nation), with differing views as to which system states are desirable. If the patterns or scales of human land use change, then the structure and dynamics of biodiversity can change accordingly. Multiple-scale analyses of spatial-temporal disturbance patterns are required not only to comprehend how a system is structured but also to formulate hypotheses about mechanisms regulating the system (Milne 1998; Brown et al. 2002).

Disturbances are particularly important to the dispersal of alien species and therefore the spatial distribution of risk of competition from alien species (With 2004). Poor dispersers spread more in landscapes in which disturbances are concentrated in space ('contagious' disturbance), whereas good dispersers spread more in landscapes where disturbances are small and dispersed ('fragmented' disturbance) (With 2004). Because disturbances may be imposed at multiple scales, species could be affected in different ways by disturbance in the same place, and a potentially useful way to appreciate these differences is to look at how disturbances are patterned in space at multiple scales (Zurlini et al. 2006a, b).

We present a conceptual model that describes land use disturbances in the spatial pattern domain and then links that information to actual land use in the geographic domain. The model considers composition and configuration as the two fundamental components of disturbance pattern (Li and Reynolds 1994). Each location on a map is characterized by the amount and configuration of disturbance within the surrounding landscape, for several landscape sizes. Different types ('profiles') of multi-scale disturbance are then identified, and mapped into the geographic domain to identify the sub-regions with characteristic patterns and scales of disturbances. We exercise the conceptual model with simulations of disturbance on neutral (Gardner et al. 1987) habitat maps, and demonstrate the interpretive power by examining actual disturbance maps in the Apulia region of south Italy. The results are discussed in the framework of disturbance management with a view towards understanding how disturbances might impact biodiversity through habitat modification.

The conceptual model

We adopt the Pickett and White (1985) definition of disturbance as ''any relatively discrete event in space and time that disrupts ecosystem, community, or population structure and changes resources, substrates, or the physical environment.'' Since habitat is defined partly by vegetation, we measure disturbance by any detectable alteration of vegetation. This includes relatively major disturbances such as the conversion of forest to agriculture land and relatively minor disturbances such as agricultural crop rotation.

Consider a binary map showing pixels of disturbed and undisturbed areas for some geographic region, and let composition refer to the amount of disturbed area and configuration to its spatial arrangement. One way to describe multi-scale disturbance patterns uses an overlapping moving window device to measure and map composition, i.e. the probability of disturbance (P_d, the proportion of pixels that are disturbed) for different window sizes over the entire region. For any given location, the changes in P_d over window size describe the local spatial pattern of disturbance surrounding that location (Milne 1991). For example, a small window with high P_d combined with a large window with low P_d implies a local heavy disturbance embedded in a larger region of fewer disturbances. As a measure of configuration, we use the adjacency of disturbance within a window, defined as the probability that a disturbed pixel is adjacent to another disturbed pixel (P_{dd}), which is also measured and mapped with a moving window device. Taken together, P_d and P_{dd} can describe a wide range of spatial patterns that are encountered on real maps (Riitters et al. 2000).

Now consider the location of a given pixel in the disturbance pattern space described by P_d and P_{dd} (Fig. 1). The location in pattern metric space summarizes the pattern of disturbance surrounding that pixel in geographic space. For example,

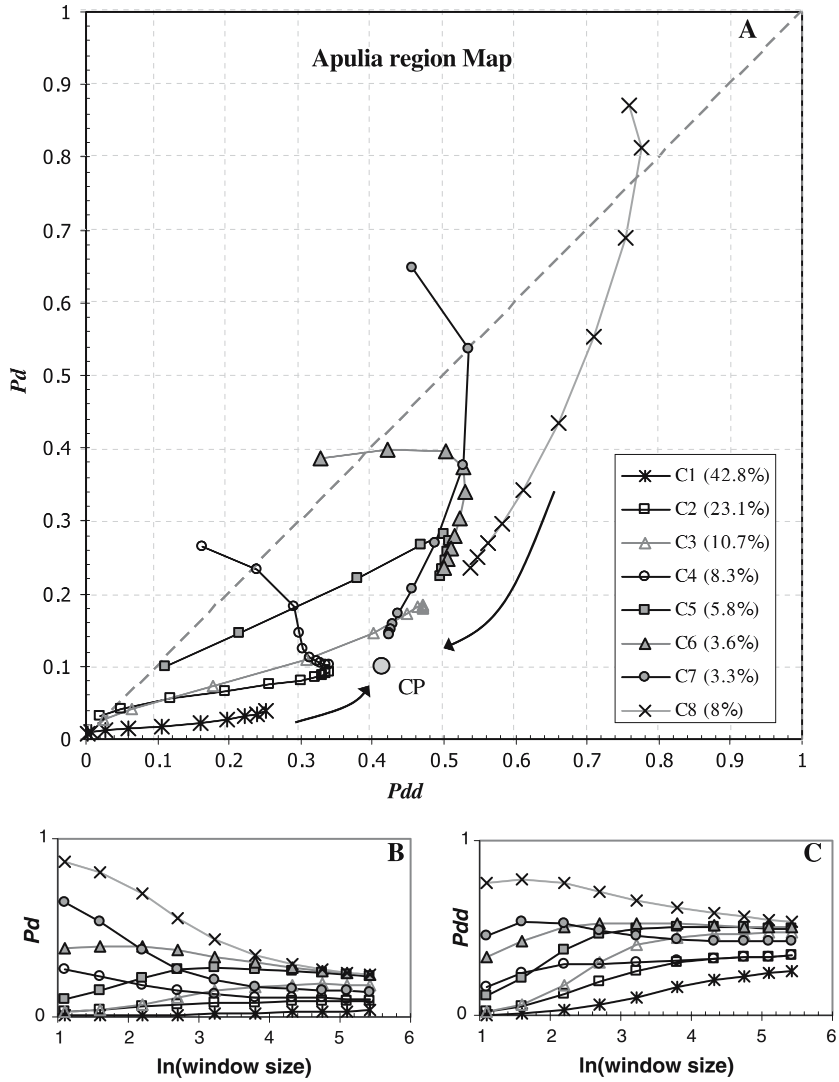


Fig. 1 Conceptual model of disturbance profiles illustrated for the Apulia region with an overall disturbance level of 10%. See text for additional explanation. (**A**) Eight disturbance profiles with arrows indicating convergence towards a regional convergence point (CP) of $[P_d, P_{dd}] = [0.10, 0.42]$; (**B**) Univariate trajectories of P_d; (**C**) Univariate trajectories of P_{dd}. (adapted from Zurlini et al. 2006a)

places that are near the upper left corner experience relatively higher disturbance levels and the disturbances do not have a high degree of spatial autocorrelation, whereas places near the lower right corner experience a lower disturbance level and disturbances tend to be more clumped within the window. When the $[P_d, P_{dd}]$ values for a fixed window size are plotted for all pixels in a given geographic region, the resulting three-dimensional frequency distribution describes the types and variety of disturbance patterns experienced by different places in geographic space. For example, more of the $[P_d, P_{dd}]$ pattern space is occupied if there are a larger variety of patterns in the geographic space, and the peaks in the frequency distribution identify the most common disturbance patterns. The distribution of observations in $[P_d, P_{dd}]$ space will naturally change with window size because changing the window size translates to sampling the disturbance map at a different spatial frequency.

A critical component of the conceptual model is the ‘convergence point’ (CP) which represents the global or background $[P_d, P_{dd}]$ value for the ideal window that is exactly equal to the entire geographic region. For any smaller window, the value of $[P_d, P_{dd}]$ will necessarily depart from the CP if the local pattern at the scale of the window size is different from the global pattern. With decreasing window size at a given geographic location, the trajectory away from the CP in [P_d, P_{dd}] space describes the multi-scale 'profile' of disturbance pattern surrounding that location. Any two geographic locations with the same trajectory experience the same multi-scale disturbance profile. This conceptual model thus identifies characteristic disturbance profiles in pattern metric space, and maps those profiles in geographic space.

For the sake of simplicity in this demonstration, we use a cluster analysis to group locations according to similarity of P_d profiles over the entire range of window sizes as the first step of implementation. The second step involves finding the average P_{dd} values corresponding to the cluster centroids, and plotting the resulting trajectories for each cluster in [P_d, P_{dd}] space. The third step is to interpret the meanings of different types of trajectories in terms of abstract disturbance profiles and the final step is to map the clusters back to the geographic space so that the physical locations of pixels in different clusters can be interpreted in terms of the real world. The utility of this approach can be gauged if there is a parsimonious interpretation of the clusters in both abstract pattern space and real geographic space. We also compare real-world results with simulated results to further understand the spatial structure of disturbances and to suggest the patterns of the processes that have created structure in the landscape.

Materials and methods

Simulating multiscale disturbance patterns

Simulated (neutral) landscape models have evolved from simple random landscape maps (Gardner et al. 1987) to maps with hierarchical structure (O'Neill et al. 1992; Lavorel et al. 1993) to investigate the 'pattern-process hypothesis' and examine how, for example, disturbance affects the dispersal of organisms and risk of extinction as a consequence of fragmentation (e.g., With and King 1997; With 2004). We used the RULE software (Gardner 1999) to generate simulated landscape maps of size 1024×1024 pixels for which the overall P_d was 0.2, a value chosen for comparability with disturbance levels on real maps (see below). In a random neutral model, there was no spatial correlation among the pixel values representing disturbance. In a multifractal model, the degree of spatial contagion was adjusted (RULE parameter H) to produce disturbances that were either dispersed ($H = 0.1$) or aggregated ($H = 0.3$) (Fig. 2). For the hierarchical ('curdled') model, the RULE parameters describe the number of units (m_i) at each hierarchical level i, and the fraction of disturbed units (p_i) at each level. We tested one three-level map for which (m_i, p_i) = (16, 0.5), (8, 0.5), and (8, 0.8) and one two-level map for which (m_i, p_i) = (16, 0.8), (4, 0.25) and with the last level for which (m_i, p_i) = (16, 1.0) (Fig. 2).

On each simulated map, P_d and P_{dd} were measured using ten window sizes of 3×3, 5×5, 9×9, 15×15, 25×25, 45×45, 75×75, 115×115, 165×165, and 225×225 pixels. As a result, there were 20 surface maps of P_d or P_{dd} for each of the simulated maps. The clustering was performed using the ten P_d maps for each simulated map, with an unsupervised k-means algorithm (an iterated centroid sorting algorithm; Legendre and Legendre 1998). Recognizing that any clustering solution is at least partly arbitrary, we specified the identification of eight clusters after experimenting with other alternatives. The average P_d and P_{dd} values of the pixels in each of the eight clusters were then calculated at each of the ten window sizes. These average values (cluster vector means) define the trajectory of each cluster at multiple scales in [P_d, P_{dd}] space. Other interpretive aids were prepared, including a table showing the percentage of pixels in each cluster, and plots of cluster average P_d and cluster average P_{dd} in relation to window size. We also examined the coefficient of variation for cluster means for each window size.

Real-world multi-scale disturbance patterns

Zurlini et al. (2006a) provide details about the 1,936,000-ha Apulia region in southern Italy. The land-use as shown by the CORINE (CLC) map (Heymann et al. 1994) indicates that 82.4% of the region is devoted to agro-ecosystems (Table 1). Six cloud-free Landsat Thematic Mapper 5 and two Enhanced Thematic Mapper Plus images

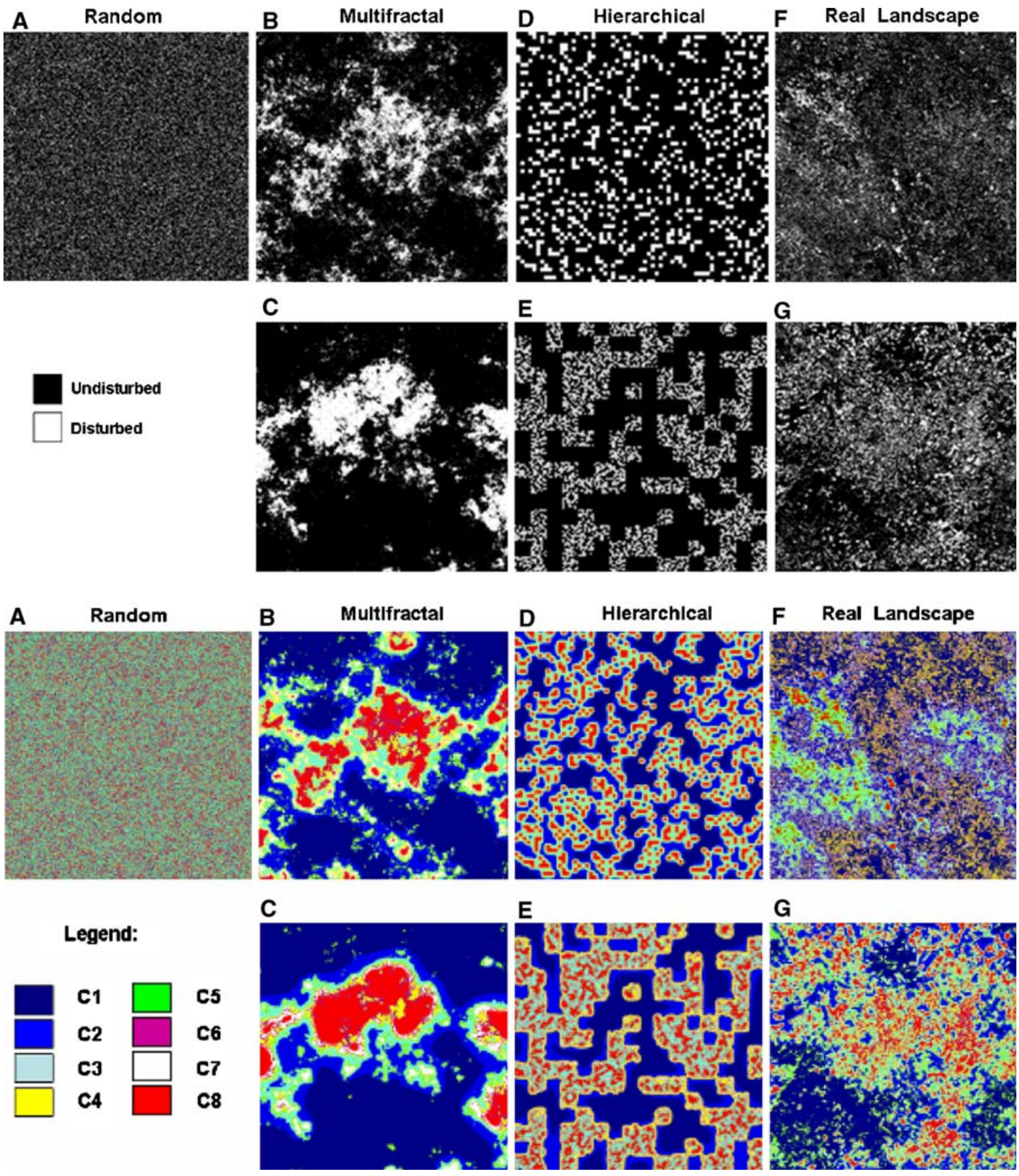


Fig. 2 Top: Simulated and real maps used as examples for the analysis of disturbance pattern at multiple scales. (**A**) random map; (**B**) multifractal map, $H = 0.1$; (**C**) multifractal map, $H = 0.3$; (**D**) two-level hierarchical map; (**E**) three-level hierarchical map; (**F**) Lecce with $P_{\mathrm{d}} = 0.202$; (**G**) Foggia-Bari with $P_{\mathrm{d}} = 0.246$. Bottom: The geographic distribution of eight disturbance profiles (see text) for the simulated and real maps

were used to map disturbance for the entire Apulia region from June 1997 to June 2001. The normalized difference vegetation index (NDVI; Goward et al. 1991) is an indicator of photosynthesis (Young and Harris 2005), and we define disturbance as a change (an increase or a decrease) in NDVI that exceeds some specified threshold value.

Table 1 Main CORINE land cover classes and class percentage composition for the Apulia region and its five administrative provinces. For each class percentages were calculated as related to the terrestrial surface of the administrative unit with the exclusion of inner water bodies and wetlands

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	1.4	56,185	2.9
Discontinuous urban fabric	1.4, 1.1.2	1.2	0.8	1.1	1.7	0.3	16,569	0.9
Arable land	2.1	29.5	26.9	32.1	27.4	58.0	758,729	39.8
Olive groves	2.2.3	30.7	45.6	38.4	11.4	6.6	419,676	22.0
Permanent crops	2.2.2, 2.2.1	7.8	5.4	5.7	13.1	5.8	137,007	7.2
Complex cultivation patterns	2.4.2	14.1	12.9	9.4	20.1	3.1	192,056	10.1
Heterogeneous agricultural areas	2.4.1, 2.4.3, 2.4.4	2.8	2.4	3.0	4.9	3.4	62,405	3.3
Forests	3.1	3.9	1.1	1.2	7.5	14.0	140,689	7.4
Shrub and/or herbaceous vegetation associations	3.2, 3.3	7.1	1.5	3.7	9.9	7.4	124,101	6.5

[a] Inland and costal wetlands (CORINE code 4.1, 4.2), Inland and marine waters (CORINE code 5.1, 5.2) were ignored in percentage and area computation

For each image, we performed the usual registration, calibration, and atmospheric corrections before calculating NDVI for each pixel. As the change over time in NDVI is a continuous variable, it is necessary to define a threshold of change to obtain a binary (i.e., change, no change) map. This choice is arbitrary since more or less of the map will be classified as disturbed if a different threshold is used. We set the threshold corresponding to a fixed percentile of 10% of both tails of the empirical distribution of standardized differences (Zurlini et al. 2006a) which guarantees that $P_{\mathrm{d}} = 0.2$ and includes equal numbers of pixels of NDVI increase and decrease. We then measured P_{d} and P_{dd} and performed the same cluster analysis as described above for the entire region and for two smaller maps (Lecce and Foggia-Bari) within the region. The Lecce map is characterized by small and scattered disturbances, whereas the Foggia-Bari map has clear geographic differences in disturbance (Fig. 2).

Results

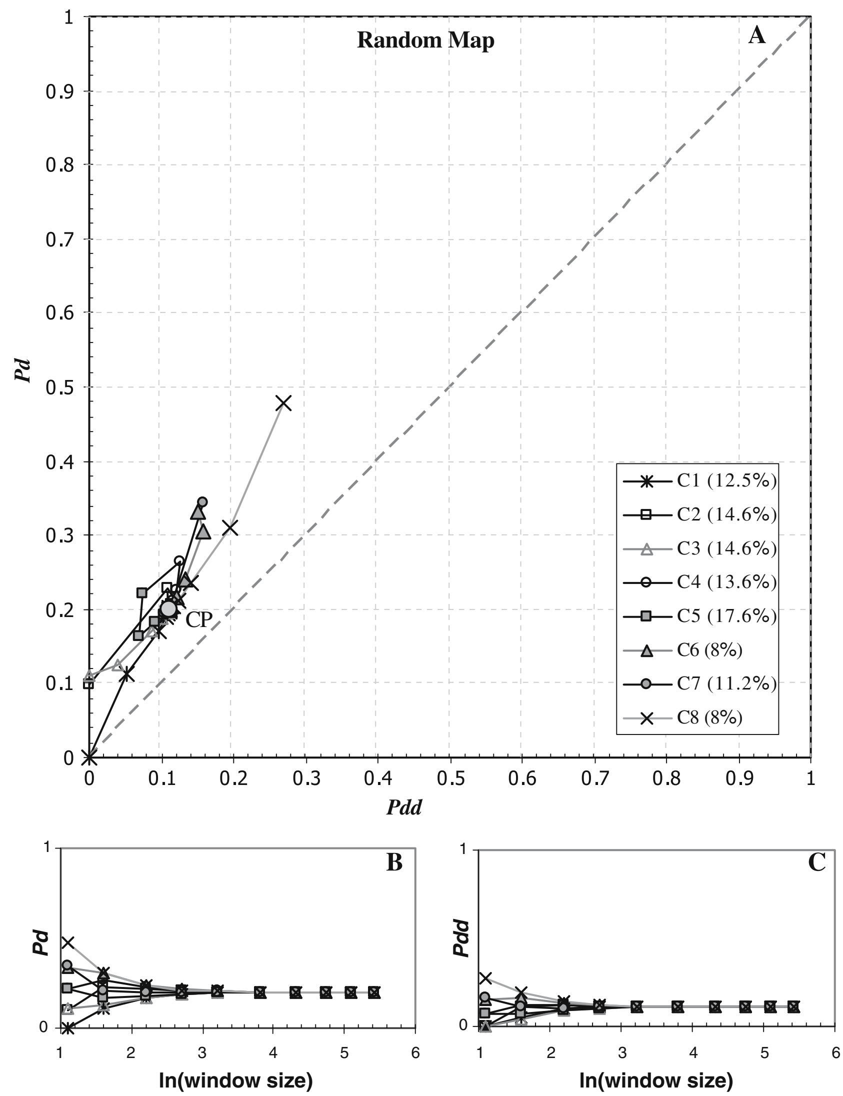
Random, multifractal and hierarchical neutral models

As expected for a map without pattern, the random map exhibited a convergence to the CP at a relatively small window size (Fig. 3) since every place on the map experiences the same disturbance pattern for a sufficiently large window. Because the 'noise' associated with small windows decreased significantly for windows larger than approximately 9×9 pixels on the random maps, the portions of the trajectories with window sizes larger than that would be more reliable when interpreting the results for the non-random maps.

The other simulated maps did not exhibit such an early convergence with increasing window size (Figs. 4–7), which generally indicates non-random multi-scale profiles. The multifractal maps (Figs. 4 and 5) exhibited the slowest convergence and none of the profiles reached the CP, whereas the hierarchical maps (Figs. 6 and 7) did exhibit a convergence for window sizes larger than those observed for the random map.

For the hierarchical maps (Figs. 6 and 7), the profiles look like strings of a frayed rope that start from different regions at the finest scales and then aggregate along scale to form a common rope given by variations in P_{d} but with P_{dd} almost constant. Cluster profiles appear as strings that approach the rope from different regions and join at different window sizes. The pattern exhibited by cluster means for P_{dd} over the range of scales (Figs. 6 and 7) suggest that the most disturbed clusters (C8 and C7) do not seem to change much along scales,

Fig. 3 Disturbance profiles for the random map. See Fig. 1 for explanation

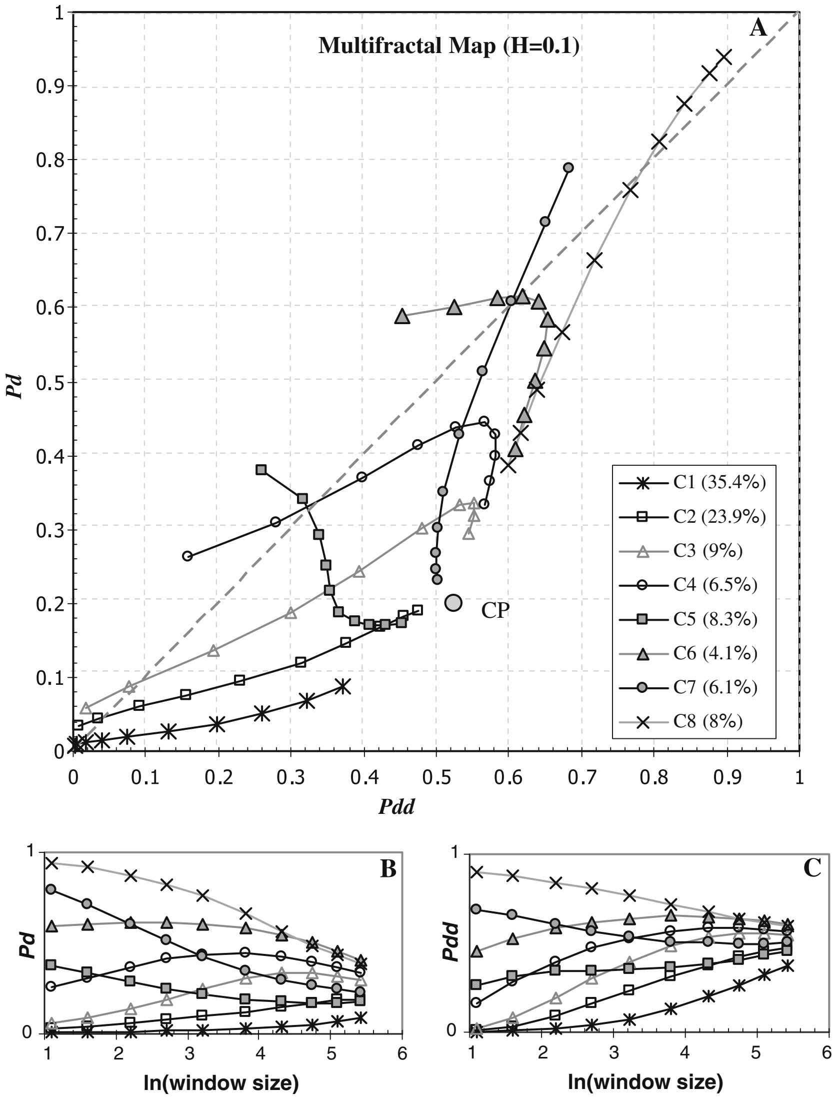


whereas the less disturbed cluster means reach the rope from below in a clear sequence of decreasing disturbance. The rope is also apparent for the random model where the strings appear when the window size approaches the grain size of the input map (Fig. 3). Clusters did not show any convergence to a common rope for the multifractal map. By definition, a multifractal is constructed to have the higher moments grow increasingly with scale, making for nonstationary parameters, which implies that cluster strings will not converge to a rope except asymptotically as window size approaches infinity.

Real world results

Mean disturbance levels (P_{d}) and connectivity (P_{dd}) for each window size for the eight clusters are shown for the maps of Lecce (Fig. 8), Foggia-Bari (Fig. 9) and the entire Apulia region (Fig. 10). In the [P_{d}, P_{dd}] metric space, the multiscale cluster strings for Lecce and Foggia-Bari are most similar to a multifractal pattern, but the rope strings are more aggregated. In the Foggia-Bari map, the rope formed by clusters 7, 6, 4, and 3 is quite evident, whereas in the Lecce map, only three strings join. Clusters in the entire Apulia region look similar to those for Lecce but

Fig. 4 Disturbance profiles for the multifractal map, $H = 0.1$. See Fig. 1 for explanation



are further from the main diagonal in the [P_d, P_{dd}] space (compare Figs. 8 and 10), and convergence occurs later and is more similar to the multifractal maps.

Geographic mapping of clusters

By definition, random maps have no local domains in either pattern metric space or in real geographic space. If the pattern is not random, then departure of a characteristic pattern from the rope signals a part of the population that is not in the same pattern space. A relevant question is then whether that pattern domain also describes a coherent geographic region. This question can be addressed since the pattern domain of each pixel is known. For the hierarchical maps, the domains of disturbance seem to describe local features (e.g., the edges of patches) and convergence is obtained in [P_d, P_{dd}] space because these local features are distributed more or less uniformly over the map (Fig. 2; Bottom, D, E). For the multifractal maps, the domains of disturbance also seem to describe local features like the cores of patches (Fig. 2; Bottom, B, C), which are distributed contagiously over the map so that convergence is obtained in [P_d, P_{dd}] space only asymptotically at the ideal window that is exactly equal to the entire

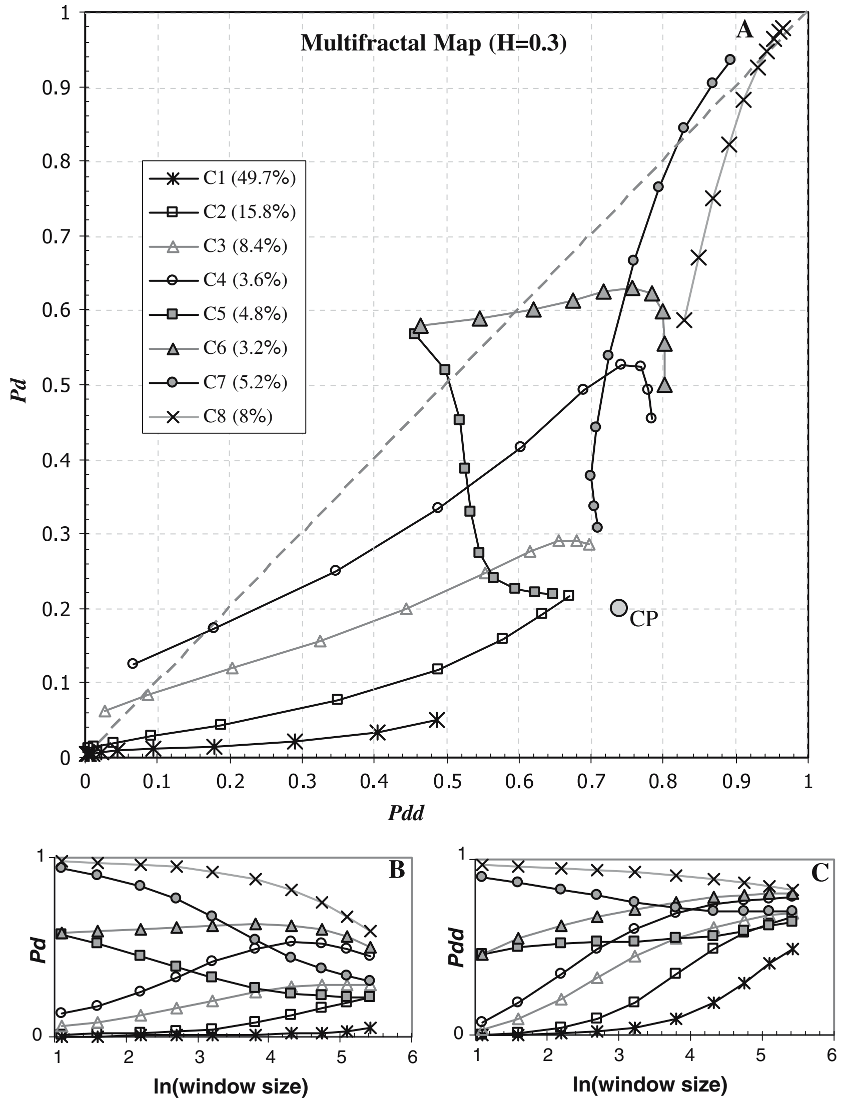


Fig. 5 Disturbance profiles for the multifractal map, H = 0.3. See Fig. 1 for explanation

geographic region. In this case, the domains of disturbance seem to describe convex and concave edges (Riitters 2005).

The cluster map of the entire Apulia region (Fig. 11) shows a clear geographic pattern. The Foggia-Bari map is at the border between two provinces with two completely different disturbance patterns which leads to a clear ''rope effect.'' In contrast, three cluster strings join in the Lecce map but rope formation is questionable. On this basis, we can speculate that there is hierarchical structure in disturbance pattern in Foggia-Bari but not in Lecce. The Apulia region as a whole encompasses Foggia-Bari and Lecce and it is therefore logical that its trajectory is intermediate in pattern metric space (Fig. 10).

Land-cover correlates of disturbance patterns

If land use were the only factor determining disturbance profiles, then each land use would tend to appear in only a few clusters. Table 2 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

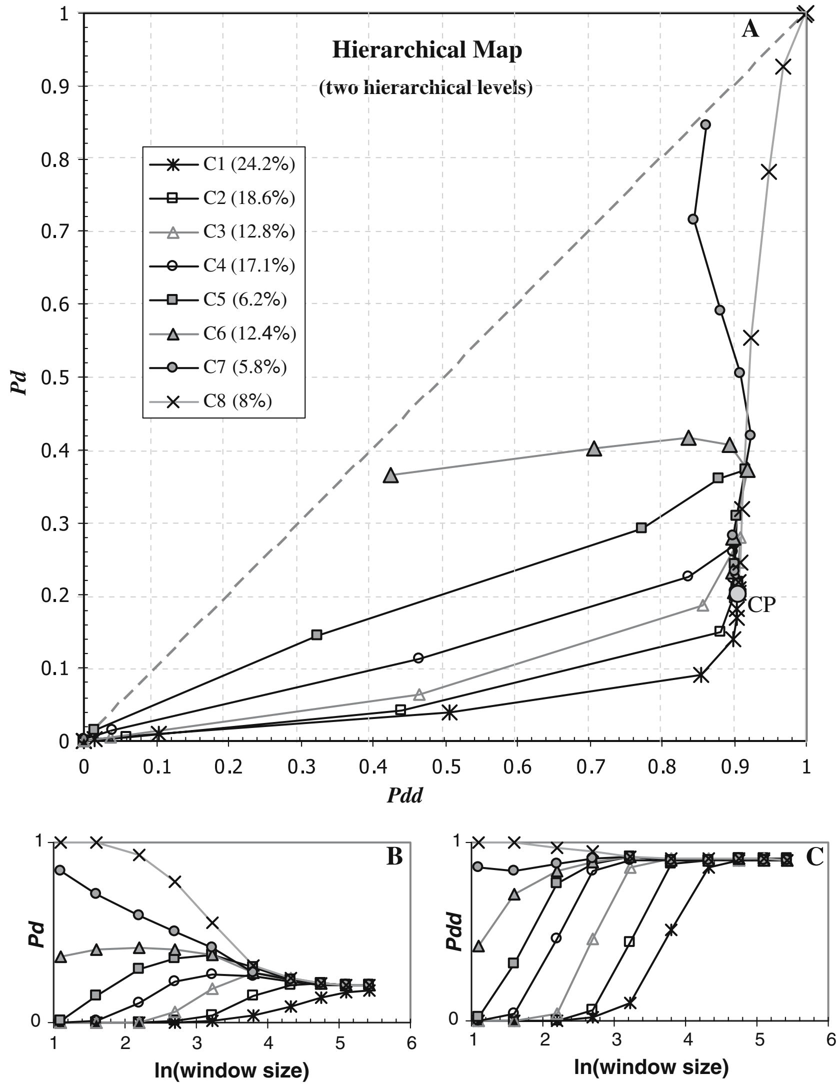


Fig. 6 Disturbance profiles for the two-level hierarchical map. See Fig. 1 for explanation

groves, which contribute most to cluster 1, and arable land, which forms most of cluster 8.

We compared the overall percentage of a given land use (Table 1) with the percentage in a given cluster (Table 2). If disturbance was distributed randomly in space, 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 model II designed *G*-test of independence for the *RxC* frequency table (Sokal and Rohlf 1995) of clusters and land uses (Table 2) with fixed column totals of 500 locations randomly sampled within each cluster, is found highly significant ($G = 943.43$; df = 63; $P < 0.001$) indicating that disturbances at multiple scales are not distributed randomly among land uses, suggesting it is worthwhile to interpret geographical patterns of disturbance in terms of the geography of land use.

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. Clusters 1 and 2, which together comprise more than 50% of the region (Table 2), have disturbance profiles indicating a relatively low degree

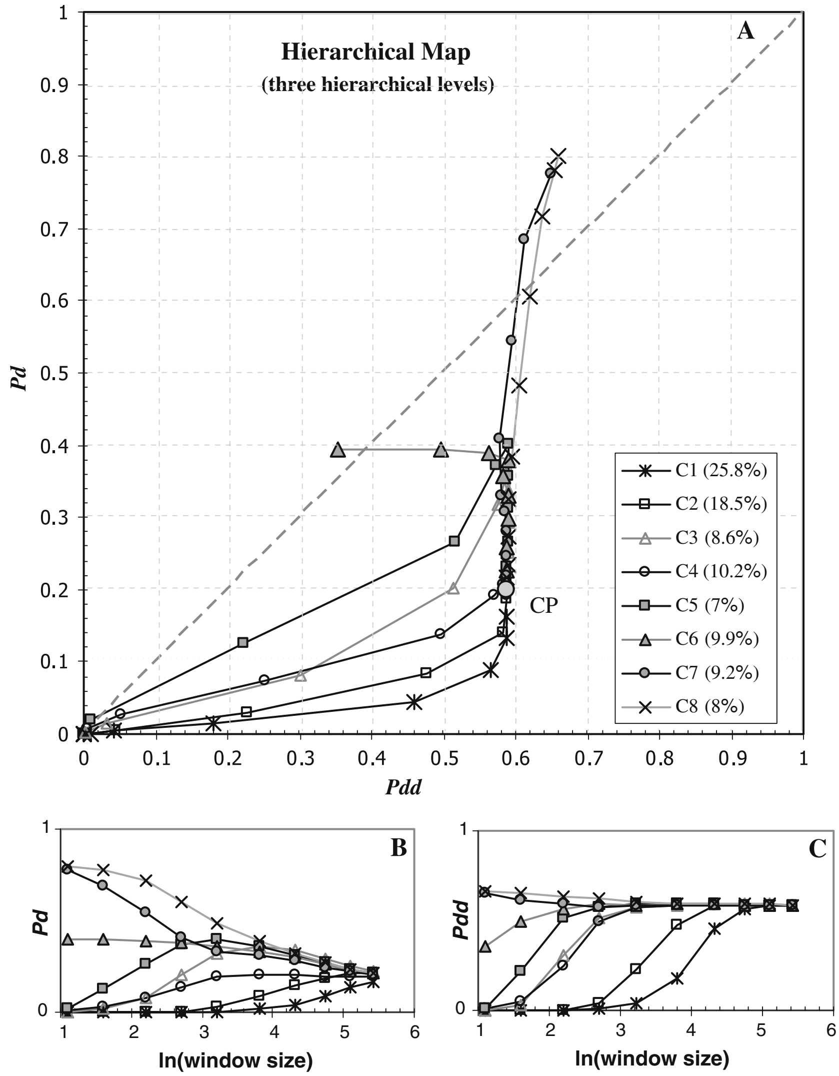


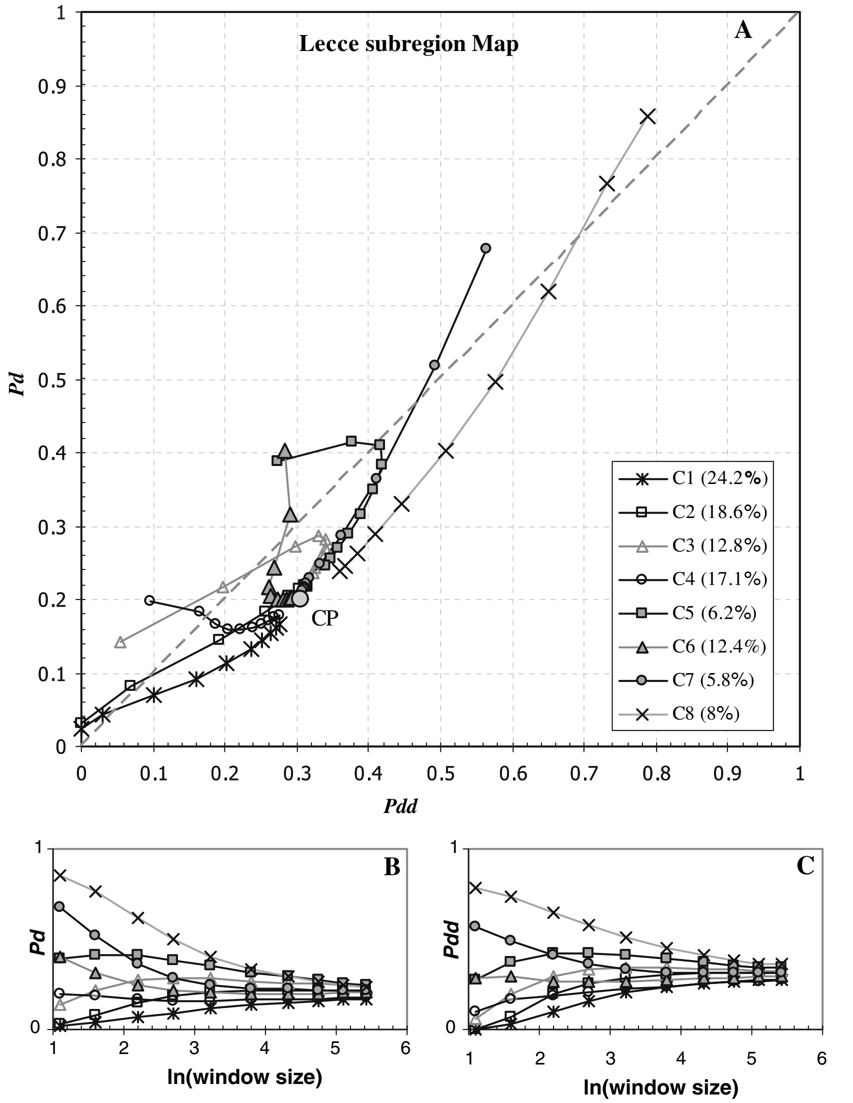
Fig. 7 Disturbance profiles for the three-level hierarchical map. See Fig. 1 for explanation

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 P_d values for small windows, implying the locations contained in those clusters are themselves disturbed, and for these clusters the decrease in mean P_d is quite rapid with increasing window size, also implying that the disturbances are widespread and isolated. The other clusters 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.

Discussion

The simultaneous consideration of time and space in both the pattern metric space domain and geographic space is essential in order to manage spatial patterns in socio-ecological systems. Our conceptual model is one way to approach the problem in a way that permits comparisons of human activities within and between landscapes. The relation between disturbance patterns and land uses in the Apulia region indicates that disturbances at multiple scales are not distributed randomly among land uses and at the same time, there is evidence for a geographical pattern of

Fig. 8 Disturbance profiles for the Lecce map. See Fig. 1 for explanation



disturbance. However, the multi-purpose CORINE land-cover map might not be the best basis to identify and interpret disturbances. Ideally, an interpretive map would show the specific land uses that are hypothesized to cause different profiles of disturbance.

The model can be used to understand the effects of landscape structure on processes such as dispersal that contributes to spread of invasive species. The critical level of disturbance at which this dispersal occurs depends upon the spatial pattern of the disturbance and the dispersal abilities of the species (With 2004). For example, consider a species that spreads through adjacent pixels of disturbed habitat. What is the implication of attempting to disperse from geographic locations that lie in different places in [P_d, P_{dd}] space? For fixed P_d, a low P_{dd} value would be better for 'interior' dispersers and a high P_{dd} would be better for 'edge' dispersers. These differences can be mapped as different clusters according to our conceptual model, and landscapes that do not occupy certain parts of the [P_d, P_{dd}] space would be less likely to experience some types of dispersal. On random maps, percolation theory (Stauffer and Aharony 1992) helps to identify critical values of P_d for interpreting the dispersal of invasive species. If

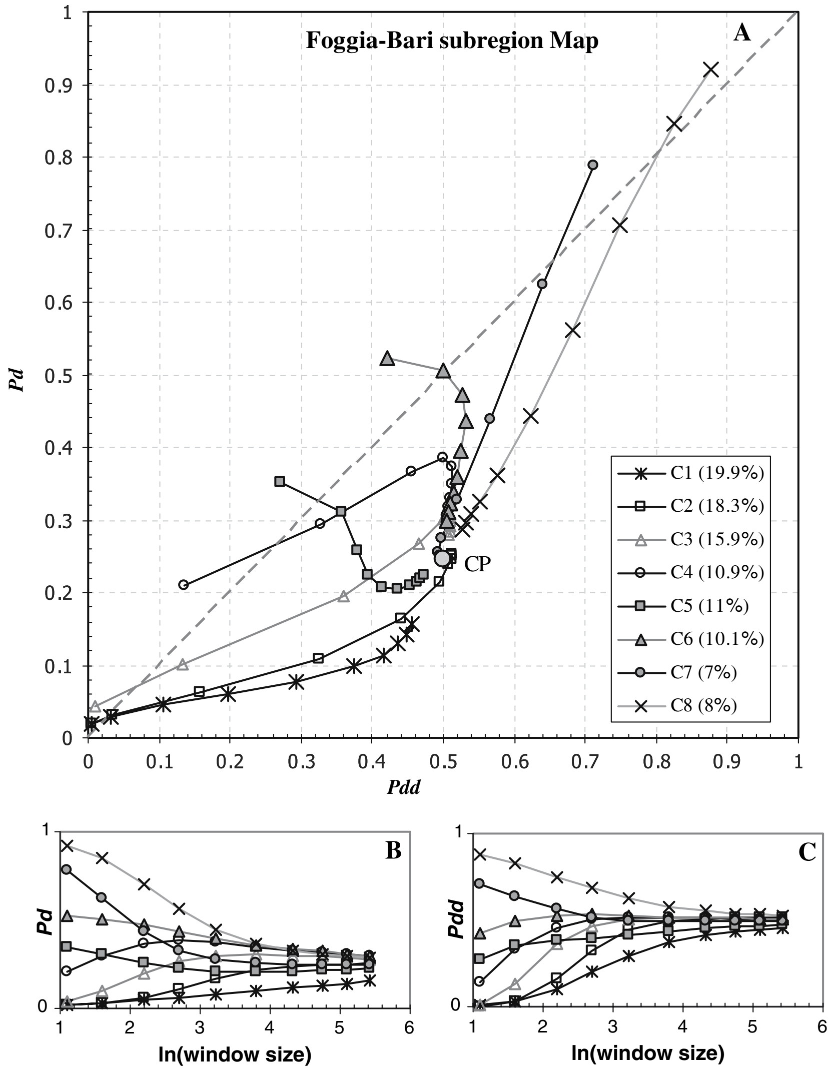


Fig. 9 Disturbance profiles for the Foggia-Bari map. See Fig. 1 for explanation

disturbances are random, the critical level of disturbance at which invasive spread occurs is $P_d \geq 60\%$ and the effective distance is defined by the window sizes corresponding to the portion of a cluster trajectory that lies above that threshold level in [P_d, P_{dd}] space. Invasive spread occurring at lower levels of disturbance, when disturbances are large or clumped in distribution on the landscape (With 2004), corresponds to portions of trajectories with very high P_{dd} values in [P_d, P_{dd}] space.

With (2004) concluded that the critical threshold of invasive spread occurs when 0.57 (P_d) of the landscape has been disturbed, if disturbances are small and localized at multiple scales (lower P_{dd} as in random, some multifractal models and real maps), but at only 0.43 (P_d) when disturbances are larger or more concentrated in space, that is at relatively higher values of P_{dd} like in hierarchical models and for the real map of Foggia-Bari border. If the invasive species has better dispersal abilities and is able to cross gaps of unsuitable habitat (e.g., single pixels of undisturbed habitat), then invasive spread on landscapes in which disturbances are small and localized is more likely to occur when only 0.26 of the landscape has been disturbed (With 2004).

We can extend discussion on the implications of hierarchical structured disturbance in the [P_d, P_{dd}] space for invasive species dispersal. The

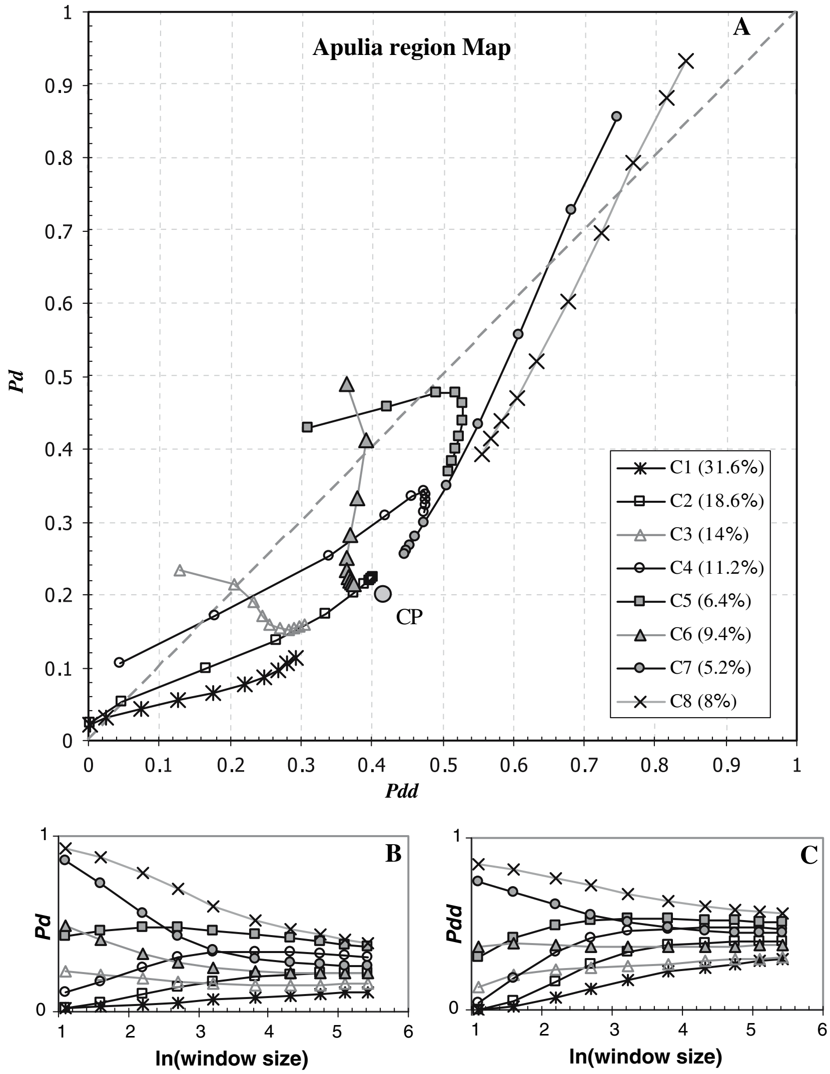


Fig. 10 Disturbance profiles for the Apulia region map. See Fig. 1 for explanation

''rope effect'' starts approximately at the percolation thresholds for ''good disperser'' in a region where whatever is undisturbed is clumped and where disturbances are large or concentrated in space. In the ''rope'' area in the [P_d, P_{dd}] space invasive species can experience an undisturbed matrix perforated by patches of disturbance with the same clumping at multiple scale for a large range of disturbances (P_d). We can appreciate that good dispersers could reach the ''rope'' from different local scale regions in the [P_d, P_{dd}] space characterized by different disturbance densities.

Since different ecological processes appear to dominate at different spatial-temporal scales (O'Neill et al. 1986), multi-scale studies have given increasing emphasis to the identification of scale domains (Brown et al. 2002). Scale and structuring of disturbance is at issue in this paper, and disturbance density and connectivity through the P_d and P_{dd} metrics and phase space can be useful to support landscape assessment and interpret fragility and risk monitoring (Zurlini et al. 2006a). In this paper, we have shown a way to characterize disturbance density and connectivity in a manner that could be very informative with respect to actual patterns on the ground, and interpretable with respect to domains of scale which are relevant to complexity theory related to land use dynamics, habitat composition, and biodiversity in socio-ecological landscapes. If we

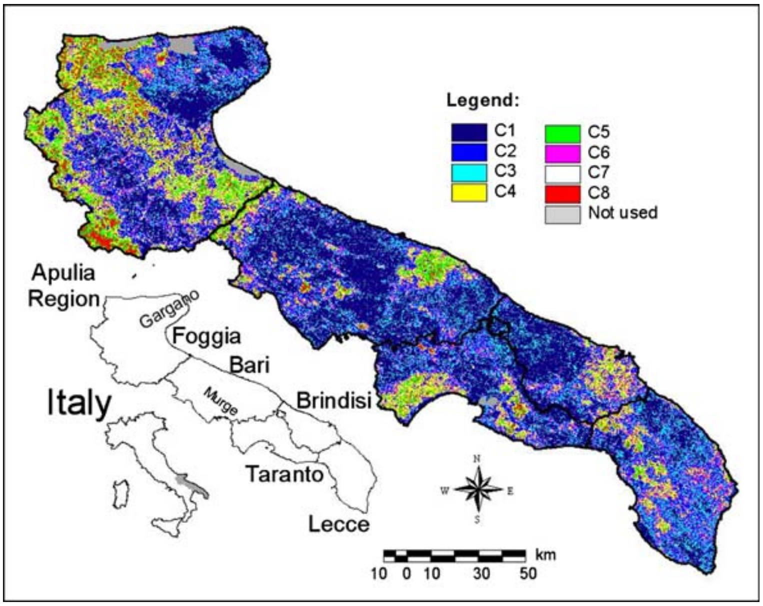


Fig. 11 The geographic distribution of eight disturbance profiles (see text) for the Apulia region

Table 2 Cluster percentage importance and cluster percentage land cover composition as derived by the CORINE land cover data base for the eight clusters identified in the Apulia region for the disturbance map with $P_d = 0.2$

Description	CORINE codes	Cluster							
		C1	C2	C3	C4	C5	C6	C7	C8
Continuous urban fabric	1.2, 1.3, 1.1.1	2.81	4.35	5.27	1.56	0.38	2.77	0.67	0.21
Discontinuous urban fabric	1.4, 1.1.2	0.74	1.01	1.87	0.51	0.15	1.06	0.31	0.02
Arable land	2.1	32.42	45.99	28.39	46.42	46.71	37.21	52.48	72.10
Olive groves	2.2.3	37.63	18.62	26.96	6.92	2.99	15.56	6.79	1.44
Permanent crops	2.2.2, 2.2.1	0.63	3.57	3.31	17.06	26.19	10.98	15.92	12.34
Pastures	2.3	–	0.01	–	0.01	0.06	–	0.02	0.06
Complex cultivation patterns	2.4.2	6.74	9.87	12.81	13.99	10.23	14.89	11.10	3.56
Heterogeneous agricultural areas	2.4.1, 2.4.3, 2.4.4	2.82	2.87	3.92	3.68	4.13	4.01	2.95	2.63
Forests	3.1	7.56	7.60	9.54	6.28	6.13	7.51	5.13	4.51
Shrub and/or herbaceous vegetation associations	3.2, 3.3	7.92	5.91	7.49	3.53	3.00	5.83	4.51	3.12
Percentage of cluster on total area		31.75	18.61	14.03	11.16	6.34	9.33	5.17	3.61

focus on the way a CP is reached in the [P_d, P_{dd}] space by trajectories of different cluster means (i.e., on the geometry of the profiles), we can identify sharp shifts in [P_d, P_{dd}] space that may indicate boundaries of scale domains in either real or simulated landscapes. Such domains are self-similar intervals of the scale spectrum over which, for a particular phenomenon, patterns do not change or change monotonically with scale. As to disturbance in a landscape, disturbance domains can indicate a substantial change in processes generating and maintaining landscape disturbance pattern at different scales (Krummel et al. 1987; Sugihara and May 1990; Milne 1991). The likelihood of sharp shifts is often linked to ecosystem resilience, which is the capacity of a system to undergo disturbance and maintain its functions and controls (Gunderson and Holling 2002). 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.

Holling (1992) proposed that landscape pattern is generated by the interaction of a few keystone processes that operate at separate and distinct spatial and temporal scales. He argued that these keystone processes entrain other ecological processes and variables to the characteristic frequencies of these processes. As a consequence, the properties of ecosystems should exhibit discrete rather than continuous structure. Holling et al. (1996) suggested that contagious disturbance processes are typical examples of keystone processes that produce discrete ecological patterns. In Apulia, disturbance events appear to be dynamically determined by the interaction of contagious disturbance regime with the spatial configuration of the underlying landscape. The transitions to local patterns generally exhibited second-order stationarity on the neutral model maps, except for hierarchical models, but not on the real map. This suggests that management of disturbance in the study region will depend less on detailed knowledge of local spatial patterns of disturbance and more on broader-scale patterns of the drivers of disturbance.

In summary, we developed a framework that could be useful to 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. Measuring disturbance density and connectivity via moving windows is a natural way to approach landscape complexity from the perspective of ‘‘context’’ to investigate causes, processes and possible consequences of land use and decision making at various scales. The multi-scale disturbance profiles could also be interpreted with respect to defining critical support regions (scale of divergence) for the assessment and management of disturbances, and for indicating the relative fragility of specific areas. Our results provide evidence of the potential of this approach for predicting ecological effects from disturbance, for planning and managing landscape disturbance mosaics, and for identifying potential invasibility hotspots of exotic species.

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