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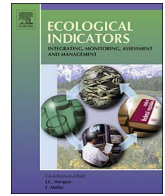
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Interpreting multiscale domains of tree cover disturbance patterns in North America

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A R T I C L E   I N F O

A B S T R A C T

Spatial patterns at multiple observation scales provide a framework to improve understanding of pattern-related phenomena. However, the metrics that are most sensitive to local patterns are least likely to exhibit consistent scaling relations with increasing extent (observation scale). A conceptual framework based on multiscale domains (i.e., geographic locations exhibiting similar scaling relations) allows the use of sensitive pattern metrics, but more work is needed to understand the actual patterns represented by multiscale domains. The objective of this study was to improve the interpretation of scale-dependent patterns represented by multiscale domains. Using maps of tree cover disturbance covering North American forest biomes from 2000 to 2012, each 0.09-ha location was described by the proportion and contagion of disturbance in its neighborhood, for 10 neighborhood extents from 0.81 ha to 180 km². A *k*-means analysis identified 13 disturbance profiles based on the similarity of disturbance proportion and contagion across neighborhood extent. A wall to wall map of multiscale domains was produced by assigning each location (disturbed and undisturbed) to its nearest disturbance profile in multiscale pattern space. The multiscale domains were interpreted as representing two aspects of local patterns – the proximity of a location to disturbance, and the interior-exterior relationship of a location relative to nearby disturbed areas.

1. Introduction

A central question in landscape ecology is how patterns and processes change with the scale of observation (Wu, 2013). A "scale domain" has been defined (Wiens, 1989) as an interval in scale space within which landscape patterns and/or pattern-process relationships are stable or predictable. Knowledge of scale domains is important because inferences made within one domain do not necessarily apply in another domain (O'Neill et al., 1986). Furthermore, if pattern regulates process, then scale domains in pattern space define constraint envelopes that regulate landscape processes occurring in those domains (O'Neill et al., 1989). Thus, knowledge of scale domains in pattern scale space is a powerful tool for describing and understanding the scaling of pattern-dependent ecological processes in complex systems (Milne, 1998; Tscharntke et al., 2006; Zurlini et al., 2006; Wheatley 2010; Zhao et al., 2016).

Progress has been limited by a tradeoff between accurate measurement of local patterns and the ability to identify scale domains. Wu et al. (2002) and Wu (2004) evaluated several pattern metrics with respect to scale domains in univariate (i.e., one metric at a time) pattern spaces. The evaluations were done at both the landscape level (Wu et al., 2002) and the focal class level (Wu 2004). Those studies concluded that if scale domains existed, they were contingent upon the choice of metric because different metrics measure different aspects of pattern. Furthermore, the metrics that were most sensitive to local patterns did not exhibit consistent scaling relations with respect to changing extent because of geographic variation of local patterns. In other words, the best metrics for measuring patterns were also the worst metrics for understanding how those patterns scaled with changing extent. That logical dilemma implied a trade-off between having a good description of patterns versus having a consistent description of how patterns changed with spatial extent.

To alleviate that trade-off, Zurlini et al. (2006, 2007) proposed a conceptual model to evaluate scaling with respect to extent while using pattern metrics that were sensitive to local patterns. By analogy to scale domains in pattern space, they considered the possibility of multiscale domains in geographic space. They demonstrated the model using binary maps of disturbed and undisturbed areas. The spatial scaling of disturbance patterns is of particular interest as a driver of complex ecological phenomena (Milne 1998). Disturbance patterns are complex
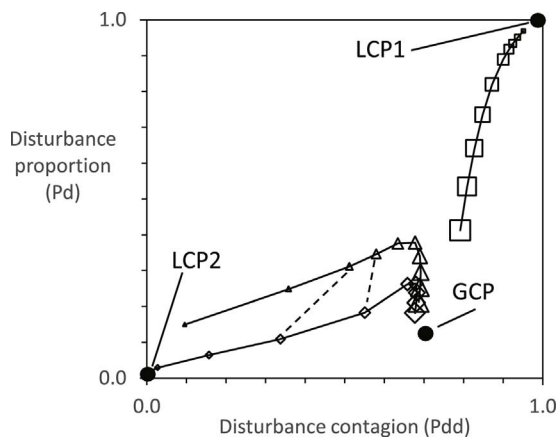
Fig. 1. The conceptual model is illustrated by three disturbance profiles in a pattern space defined by the local proportion and contagion of disturbance. Each disturbance profile connects the observed patterns across measurement extent (scale), and the size of the symbols indicates the relative extent. In addition to the global convergence point (GCP), there are two local convergence points for an extent equal to the size of one pixel that is either disturbed (LCP1) or undisturbed (LCP2). The dotted lines illustrate a "cross-scale mismatch" (Zaccarelli et al., 2008).

because disturbances have multiple causes operating over a range of spatial scales (Turner, 2005). Alternatives to the classical equilibrium paradigm must be able to define stability in terms of disturbance at multiple scales (Wu and Loucks, 1995). The conceptual model considers a pattern space defined by the proportion (Pd) and contagion (Pdd) of disturbance (Fig. 1). In that pattern space, there is a global convergence point (GCP) which is the [Pd, Pdd] value for the extent (scale) that is exactly the extent of the entire study area. For smaller extents, the observed [Pd, Pdd] departs from the GCP if the local pattern is different from the global pattern, where "local" is defined by a particular location and extent. At a given location, the trajectory away from the GCP is the "disturbance profile" which describes the scaling of pattern at that location. A "multiscale domain" is a set of geographic locations with similar disturbance profiles. Whereas classical scale domains are identified by local invariance of pattern in pattern space, multiscale domains are identified by local invariance of the scaling of pattern in

geographic space. This conceptual model made it possible to exploit the local sensitivity of pattern metrics such as proportion and contagion, by incorporating their geographic variance into the definition of a multiscale domain.

The conceptual model has a high potential for the prediction and management of disturbance-related processes such as the spread of invasive species across landscapes (Otte et al., 2007). But additional testing is needed because the model has been tested with only one disturbance map in the Apulia region of southeast Italy, for which the choice of eight disturbance profiles was arbitrary (Zurlini et al., 2006). Furthermore, the patterns represented by those disturbance profiles have been interpreted only by comparisons with profiles derived from neutral (random, hierarchical, multifractal) disturbance maps (Zurlini et al., 2007). There has not been a systematic interpretation of disturbance profiles in terms of actual disturbance patterns, and it is not clear that eight disturbance profiles are optimum for another study area large enough to contain many more types of disturbance profiles (e.g., large fires in contiguous boreal forests versus dispersed forest cutting in fragmented temperate forests). Because reliable interpretations of patterns are pre-requisite to reliable interpretation of pattern-process relationships (Bogaert, 2003), the objective of this study was to improve the interpretation of multiscale domains with respect to actual patterns using maps of tree cover disturbance from 2000 to 2012 in North American forest biomes.

2. Methods

Maps of tree cover disturbance were derived from the Global Forest Change Database (GFCD) (Hansen et al., 2013). We defined forest disturbance from the GFCD map of tree cover loss which represents stand-replacement disturbances during the period 2000–2012. The GFCD consists of a set of 10° × 10° map tiles in a geographic projection. Following procedures detailed by Riitters et al. (2016), the 55 GFCD map tiles covering North America from 20 to 80° north latitude and 50–180° west longitude were mosaicked. To ensure that the neighborhoods used in later analyses were the same size everywhere, the mosaicked map was projected to a Lambert azimuthal equal-area geographic projection with a target pixel area of 0.09 ha (to match the nominal resolution of the Thematic Mapper data that were used to
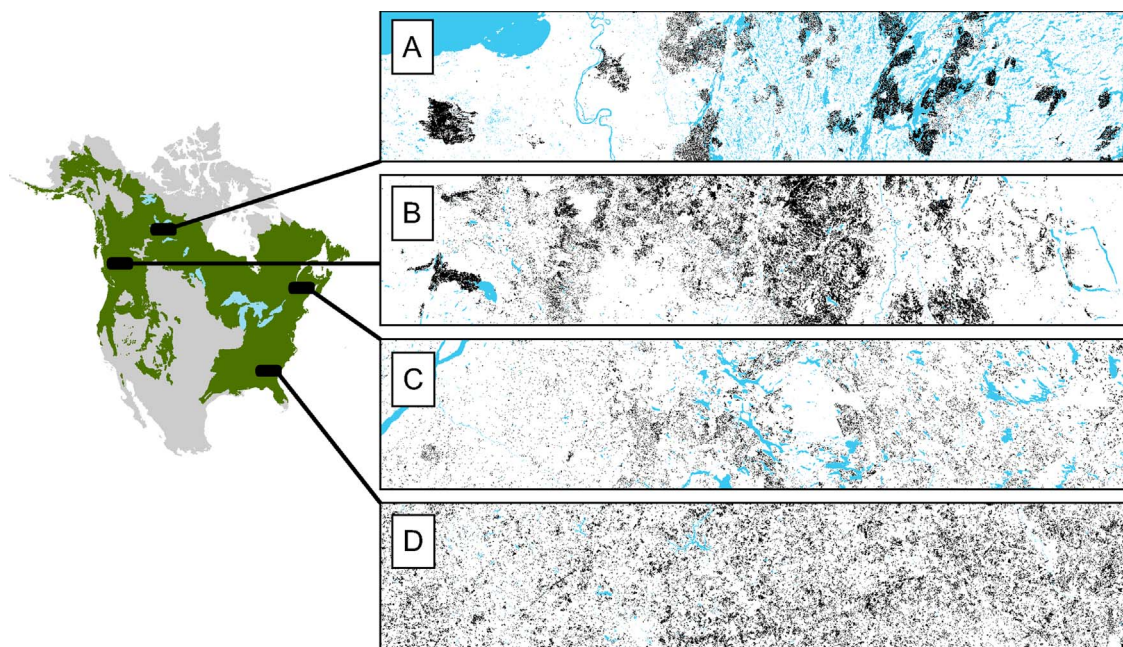

Fig. 2. Left: the study area included North American forest biomes. Right: examples of disturbed (black) and undisturbed (white) areas in (A) Northwest Territories, (B) British Columbia, (C) Maine, and (D) Georgia (water is shown in blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

produce the GFCD). The corresponding GFCD data mask map identified permanent water bodies which were subsequently ignored as missing data. This study focused on North American forest biomes (Olson et al., 2001; World Wildlife Fund 2004) (Fig. 2). Excluding missing data, the study area was approximately 9.574×10^6 km^2 (10.6×10^9 pixels), of which approximately 0.488×10^6 km^2 (5.1%) was disturbed forest cover.

To identify multiscale disturbance profiles we followed the general approach of Zurlini et al. (2006) by applying a moving window algorithm (Riitters et al., 1997) to measure and map disturbance proportion (Pd) and disturbance contagion (Pdd) over multiple spatial extents, and by using k-means clustering to identify disturbance profiles from the measurements. We improved the implementation of the conceptual model by considering a much larger study area, by explicitly including Pdd in addition to Pd in the k-means analysis, by not pre-specifying the number of clusters (k) to consider, and by interpreting results with respect to the local as well as the global convergence points.

A moving window algorithm measures and maps pattern metrics as continuous variables representing the pattern context surrounding each location. The observation scale is defined by the size (extent) of the window. Within a fixed-area window, we measured Pd by the proportion of pixels that were disturbed, and Pdd by the conditional probability that a pixel adjacent to a disturbed pixel was also disturbed (Riitters et al., 2000). Pd and Pdd were mapped by centering a window on a given pixel, calculating Pd and Pdd within the window, storing the two resulting values (on two new maps) at the location of that pixel, and then repeating the procedure by centering the window on every individual pixel in the study area. That process was repeated for 10 window sizes of 0.81 ha (3 pixels × 3 pixels), 2.25 ha (5 × 5), 4.41 ha (7 × 7), 7.29 ha (9 × 9), 15.2 ha (13 × 13), 65.6 ha (27 × 27), 2.72 km^2 (55 × 55), 11.1 km^2 (111 × 111), 44.8 km^2 (223 × 223), and 180 km^2 (447 × 447). In this way we prepared 20 surface maps, each at 0.09 ha resolution, representing the local proportion and contagion of disturbance at 10 observation scales.

We identified multiscale disturbance profiles by grouping pixels (both disturbed and undisturbed) according to similarity of Pd and Pdd across the 10 observation scales. We began by selecting a systematic 10 percent sample of non-missing locations (approximately 1.1×10^9 observations). We used a k-means clustering algorithm to group the sample of locations according to similarity of Pd and Pdd across observation scales, and tested alternate values of k when determining the number of clusters to retain. Each cluster was assumed to represent a typical disturbance profile. To interpret the disturbance profiles in pattern space, the cluster means of Pd and Pdd were plotted across observation scales in a pattern space similar to Fig. 1. To interpret the disturbance profiles in geographic space, a map of multiscale domains was constructed by assigning each location in the study area (including non-sampled locations, but excluding water) to the nearest (by 20-dimension Euclidean distance) disturbance profile.

3. Results and interpretation

3.1. Disturbance profiles and multiscale domains

With increasing extent, the cloud of data points representing individual pixels shifted towards the lower right corner of the pattern space (Fig. 3A & B). The LOESS curve through the data cloud for each extent exhibited a steady progression towards the lower right corner of the pattern space with increasing extent (Fig. 3C). The k-means procedure identified 13 disturbance profiles (Fig. 4A & B) with an overall r^2 of 0.88 (see Supplementary material). Examples from the map of multiscale domains (Fig. 5) will facilitate later interpretation of the disturbance profiles with respect to actual patterns (similar maps for the entire study area are in the Supplementary material). For the disturbance maps shown in Fig. 5A, multiscale domains are shown for
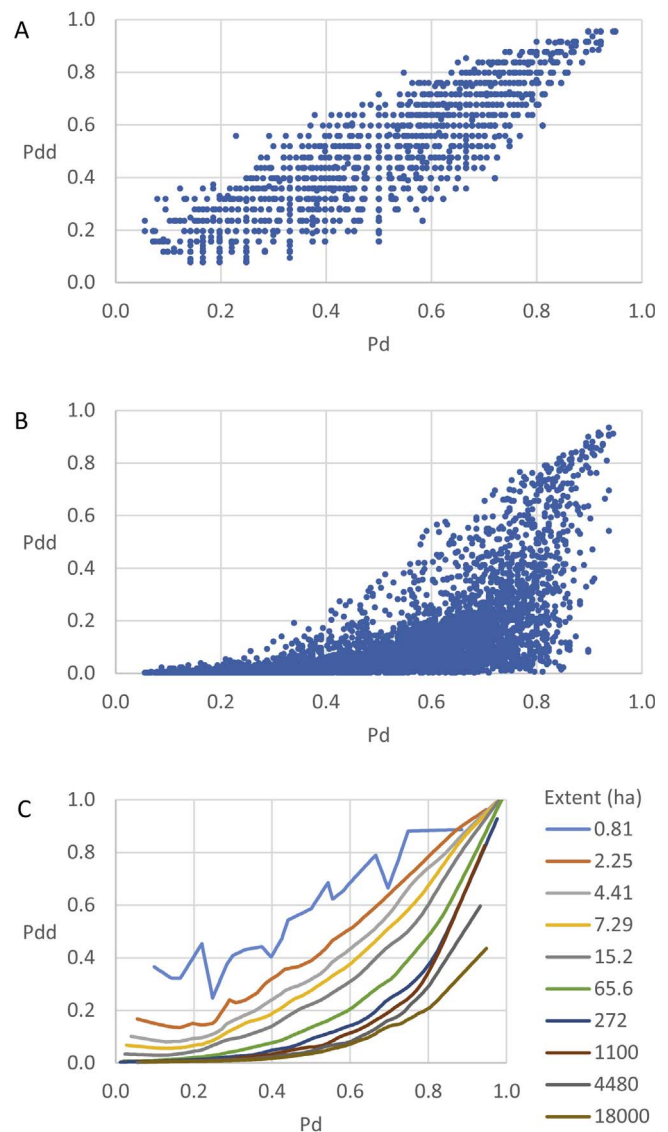

Fig. 3. The distribution of observations in pattern space is illustrated for a sample of 5000 pixels for extents of (A) 2.25 ha and (B) 1100 ha. The LOESS curves (C) through the sample observations move towards the lower right with increasing extent. Because there are fewer possible values in smaller extents, (A) appears to be less dense than (B), and the LOESS curves (C) for the smallest extents are less smooth than for larger extents. (The observations at [0,1] and [1,1] were not used for these figures.). (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

all locations (Fig. 5B), for the subset of undisturbed locations (Fig. 5C), and for the subset of disturbed locations (Fig. 5D). For comparisons to profiles in pattern space, the map legend uses the same profile colors as Fig. 4. The choice of colors is explained at the end of section 3.2.

The location of the global convergence point (GCP) can only be approximated in Fig. 4B because it was not feasible to measure the global [Pd, Pdd] value, and because there was no clear empirical GCP due to spatial variation of Pd or Pdd at scales larger than the largest extent tested in this study. As indicated in the conceptual model (Fig. 1), and as expected from the LOESS curves (Fig. 3C), the profile means became further from the GCP with decreasing measurement extent (see Supplementary material for three-dimensional perspectives of Fig. 4A). Profiles did not necessarily converge at a local convergence point ([0,0] or [1,1]) because the smallest extent tested was larger than one pixel. The Supplementary material shows that other k values were plausible, and that $k = 21$ yielded similar disturbance profiles while providing a more detailed partitioning of the pattern space.
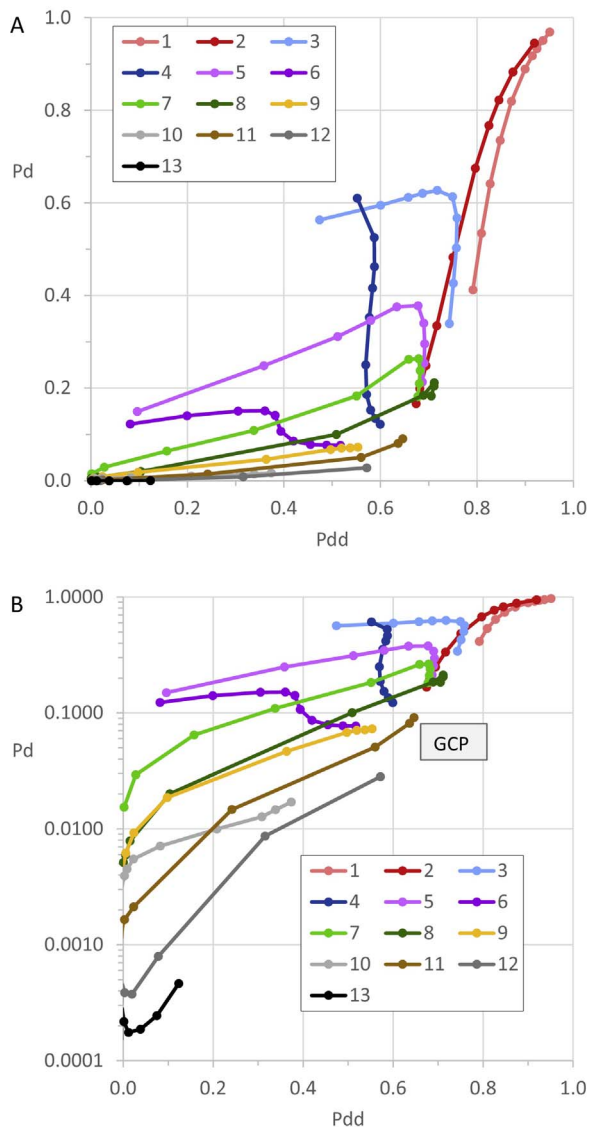
Fig. 4. Disturbance profiles in pattern space with Pd shown in (A) original scale and (B) logarithmic scale for detail. The approximate location of the global convergence point (GCP) is indicated in (B). (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

It is visually apparent (see also Supplementary material) that some of the disturbance profiles are strongly associated with either undisturbed (Fig. 5C) or disturbed (Fig. 5D) areas. Profiles 1 and 2 occur almost exclusively at disturbed locations, while profiles 7 through 13 are almost exclusively associated with undisturbed locations. Additional evidence of that fidelity is the observation that for the smallest extent, the mean [Pd, Pdd] values of those profiles are close to the local convergence point [1,1] for profiles 1 and 2, or [0,0] for profiles 7 through 13 (Fig. 4). Profiles 3 through 6 occur at both disturbed and undisturbed locations (Fig. 5C & D) and the mean [Pd, Pdd] values for the smallest extent not exhibit local convergence indicating either disturbed or undisturbed areas (Fig. 4).

3.2. Interpretation of local disturbance patterns

One aspect of pattern that was reflected in the profiles was called "proximity" in reference to the distance of a location to a locally-dense concentration of disturbed area. For example, transects from a region of much disturbance to a region of little disturbance (Fig. 5B) typically contain the sequence of profile numbers from 1 to 13 in that order.

Some profiles in that sequence may not appear in some transects if Pd was measured in an extent which contained several different disturbance locations. Apart from visual inspection, the proximity interpretation was also supported by examining the cross-scale mismatches (Zaccarelli et al., 2008) of Pd with respect to extent. A cross-scale mismatch is generally defined as a difference in the rate of change of pattern (Pd, Pdd, or both) with respect to extent (see Fig. 1). For example, Pd decreases slower with increasing extent for profile 1, which is closer than profile 2 to locally-dense areas of more disturbance. At the other extreme, for profiles 9 through 13, Pd increases faster with increasing extent for profiles that are closer to locally-dense areas of more disturbance.

The second aspect of pattern was best illustrated by the intermediate disturbance profiles (3 through 8) which appeared to capture an "interior-exterior" relationship of locations in relation to nearby disturbed areas. The interior-exterior interpretation is supported by the abrupt changes of direction of those profiles in pattern space that represented cross-scale mismatches for Pdd as well as for Pd (Fig. 4). Consider the three pairs of disturbance profiles: 3 and 4; 5 and 6, and; 7 and 8. In each pair, the first profile listed appeared to be "interior" and the other appeared to be "exterior" (Fig. 5D) in relation to nearby disturbed area. Both members of each pair had similar [Pd, Pdd] values for the smallest extent (Fig. 4). For the interior profile of each pair, Pd increased faster (and/or did not decrease) with increasing observation scale in comparison to the exterior profile. Because relatively more disturbance was included in larger extents for the interior member of each pair, that profile approached a common point at the largest extent from above (i.e., from a larger Pd value) while the exterior member of each pair approached that point from below. The cross-scale mismatches for Pdd were the reason for approaching a common point from above or below. In addition, the intermediate profiles often appeared as interruptions of the typical proximity sequence in regions containing moderate amounts of disturbed area that were not close to the largest disturbed areas. Proximity and interior-exterior relationships are partially confounded in the disturbance profiles because geometric packing constraints lead to correlation of Pd and Pdd in any fixed extent (Riitters et al., 2000). That correlation implies that proximity may also be interpreted as the degree of interior-ness or exterior-ness.

With those interpretations we can provide the rationale for the choice of profile colors in Figs. 4 and 5. A base color (black, orange, green, purple, blue, or red) was assigned to a profile depending on the location of its mean values for the smallest extent in pattern space (Fig. 4). A lighter shade of a given base color was assigned to profiles that were either interior or closer to disturbance, and a darker shade was assigned to profiles that were either exterior or further from disturbance.

4. Discussion

Reliable measurement of spatial patterns is prerequisite to interpreting the ecological causes or consequences of those patterns (Bogaert 2003). Thus, knowledge of actual disturbance patterns represented by disturbance profiles should improve our ability to interpret disturbance profiles in relation to the scaling of disturbance-related ecological phenomena. A conceptual model alone may be sufficient to interpret source/sink relationships in nested social-ecological landscapes (Zaccarelli et al., 2008), environmental security and disturbance regulation by different land uses (Petrosillo et al., 2010), or ecological resiliency in adaptive management (Zurlini et al., 2014). But knowledge of actual patterns is surely required for planning disturbances to manage biological invasions (e.g., Zurlini et al., 2013). Desirable disturbance profiles may be relatively easy to define in abstract terms, but land management plans must also be able to identify specific aspects of pattern to manage at particular locations and spatial scales. By interpreting disturbance profiles in relatively simple terms of disturbance proximity and interior-exterior relationships in geographic
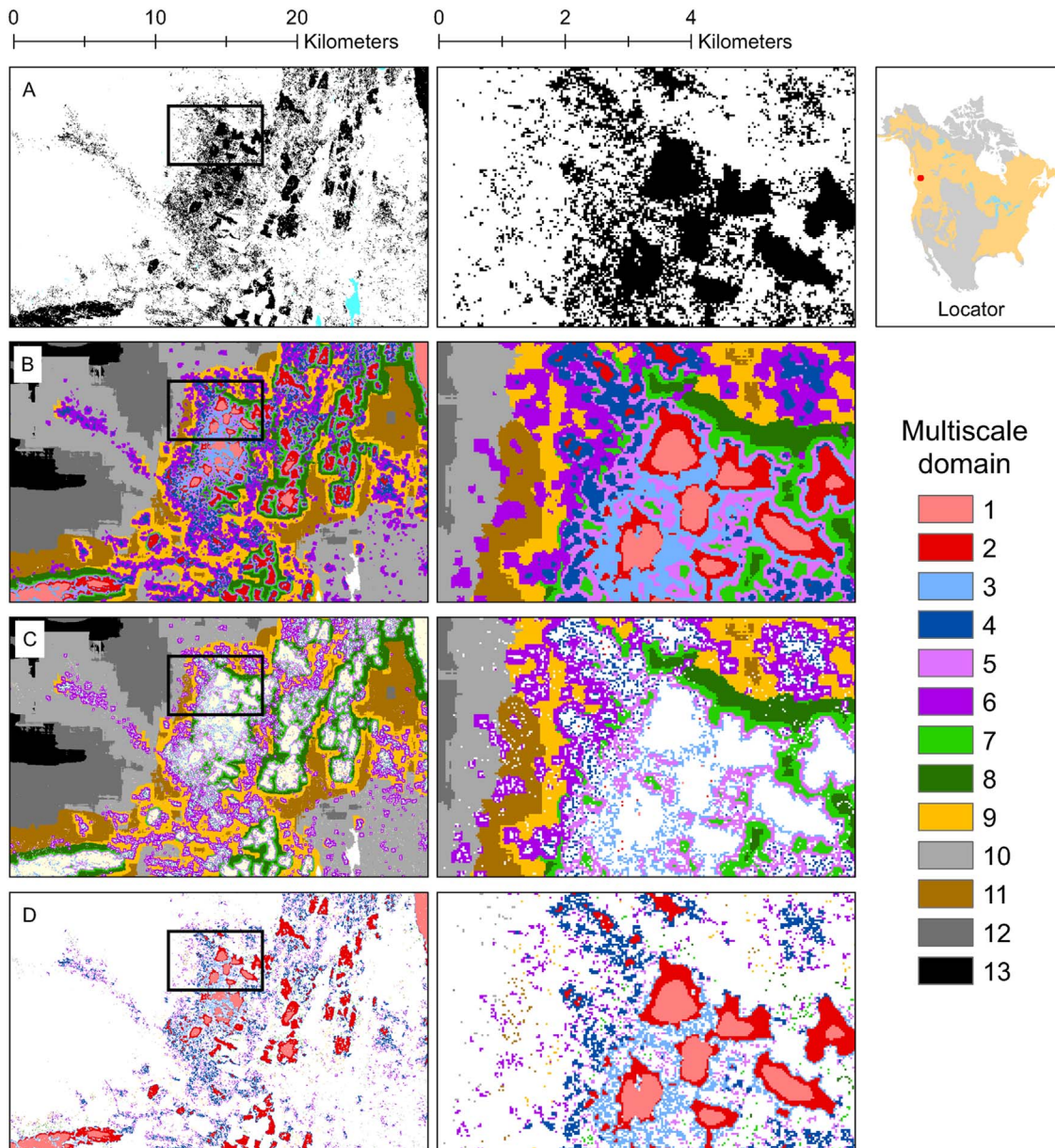
Fig. 5. Local example of disturbance multiscale domains. The left column is the area shown by the locator map; the right column is the indicated enlarged area. (A) Disturbed (black), undisturbed (white) and water (blue). Multiscale domains for all land (B), undisturbed land only (C), and disturbed land only (D). Note: the legend uses colors comparable to Fig. 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

space, our results should provide a useful alternative to planning disturbances in a higher order (e.g., 20-dimension in this study) pattern-scale space.

Our simplification of the interpretation of disturbance profiles leads directly to identification of pattern-process hypotheses that can be tested. For example, since the disturbance profiles describe relative proximity to areas of more or less disturbance, it is plausible that the risk of colonization by invasive plants from nearby disturbances is related to disturbance profiles. Similarly, since the profiles describe interior-exterior relationships in relation to previous disturbances, it is plausible that the risk of wildfire spread is related to disturbance profiles. For these applications, the disturbance profiles for sets of locations with field observations of invasive plants or wildfires could be extracted by geographic overlay from the map of multiscale domains to serve as independent variables in an analysis of the phenomenon of interest. One of the benefits of wall-to-wall mapping of disturbance profiles is that even though separate sets of observations may be extracted to address different questions, the results can still be

integrated within the same pattern-scale space. That is important because consistency of pattern measurements makes it possible for management plans to more easily consider trade-offs between competing ecological objectives.

Because pattern varies continuously across landscapes and we employed methods which measured and mapped proportion and contagion as continuous variables, we anticipated that the disturbance profiles would represent a gradient of multiscale patterns rather than a finite set of unique multiscale patterns. Thus, it was not surprising that the *k*-means procedure yielded disturbance profiles that could be interpreted as gradients of pattern in geographic space, or that the choice of a larger *k* produced a similar yet more detailed characterization of pattern space. In future work, the *k* value in *k*-means clustering may be considered as a tuning parameter controlling the desired level of detail for describing multiscale patterns.

To achieve our objective of interpreting patterns, we identified typical disturbance profiles and mapped the corresponding multiscale domains according to the relative distance (in 20-dimension pattern

space) of a given location to each of the typical profiles. Unless *k* is very large, the locations exhibiting unusual or uncommon disturbance profiles are not likely to be identified by our procedure. And yet, those locations may be interesting if, for example, they represent abrupt transitions between typical disturbance profiles. Such "jumps" in pattern space could represent abrupt boundaries or local discontinuities of patterns in geographic space. To identify such locations, we can suggest a modification of our procedure in which the assignment of a location to a typical profile is performed for subsets of observation scales, for example large extents versus small extents. The locations of interest would be those for which the assignment was scale-dependent.

We expect that similar multiscale analyses of proportion and contagion on any raster binary map will yield similar interpretations of actual patterns because the results depend more on the fundamental measurements (proportion and contagion) than on the choice of which attribute to measure. We analyzed disturbance for comparability with the original implementation of the conceptual model (Zurlini et al., 2006), and we defined disturbance in terms of tree cover loss in order to take advantage of a high-resolution continental dataset (Hansen et al., 2013). Since tree cover loss could have occurred only at locations where there was originally tree cover, the original distribution of tree cover necessarily constrained the patterns of disturbance which could have been observed (Wickham et al., 2008; Riitters and Wickham, 2012). For example, the largest Pd values could not be obtained where the original tree cover was not extensive to begin with. Our definition of disturbance was reasonable because our focus was on actual disturbance patterns no matter how they were generated or why they were constrained. Regional comparisons of multiscale domains naturally must account for differences in the constraints imposed by the original amount and pattern of the attribute of interest.

Acknowledgements

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2017.05.022.

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