Landscape Metrics, Scales of Resolution

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1 Introduction

Effective implementation of the "multiple path" approach to managing green landscapes depends fundamentally on rigorous quantification of the composition and structure of the landscapes of concern at present, modelling landscape structure trajectories under alternative management paths, and monitoring landscape structure into the future to confirm whether management is having the expected effects on landscape structure. Indeed, quantification of current conditions, anticipation of future changes and monitoring these changes as they occur are the three foundational elements of adaptive management and the key foundation for the multiple path approach to landscape design.

In this chapter we review five key components of landscape analysis. First, we discuss the importance of appropriate models of landscape structure. Second, we review the critical issue of scale and its enormous influences on landscape analysis. Third, we review the importance of evaluating the spatio-temporal context of the present landscape, and discuss several approaches to establishing it. Fourth, we define the meaning landscape metrics, review the major components of landscape pattern, and describe a number of the most useful landscape metrics for characterizing each component of landscape structure. Fifth, we discuss linking landscape analysis to simulation modelling to infer the expected effects of alternative management scenarios using landscape trajectory analysis. The topics in this chapter are adapted from much more complete treatment in McGarigal et al. (in press) and Cushman and McGarigal (2006).

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2 Defining the Model of Landscape Structure

2.1 Classification Paradigms

There are many ways to model or represent landscape structure. For example, in the *island biogeographic* model the landscape is represented as a simple binary landscape consisting of habitat patches and a background matrix. In this case, habitat is represented as occurring in discrete patches distributed in a homogeneous matrix. In contrast, the *landscape mosaic* model represents the landscape as a spatially heterogenous mosaic of several patch types. The appropriate model of landscape structure depends on the issues of importance to managers or researchers. The same landscape can be represented in many different ways, and the investigator or manager must select a model that adequately represents the landscape in a manner and scale relevant to the issues or organisms of importance.

2.2 Choice of Digital Data Format

There are different data formats for digitally representing a model of the landscape, and there are practical implications to the choice of formats. Vector and raster data formats are both commonly used in landscape analysis. Vector format represents each patch as a polygon, where the boundaries of the polygon conform to the actual boundaries of the patch in the real world. In contrast, raster format represents the landscape as a lattice of grid cells, in which each cell is assigned a value corresponding to the patch type or class comprising the majority of the cell. Patches are defined by contiguous cells of the same cover type. Because vector and raster formats represent lines differently, metrics involving edge or perimeter will be affected by the choice of formats (McGarigal et al. in press). Edge lengths will be biased upward in raster data because of the stair-step outline, and the magnitude of this bias will vary in relation to the grain or resolution of the image. The key point here is that many landscape metrics are not invariant to the data format, and some metrics are defined only for vector or raster formats. In general, the raster format has gained popularity over the vector format because of the ease of conducting complex spatial computations on grids.

3 Determining the Appropriate Scale of Analysis

Measured landscape pattern is a function of scale. To summarize McGarigal et al. (in press), the spatial scale of ecological data is defined by extent and grain (Forman and Godron 1986; Turner et al. 1989; Wiens 1989a). *Extent* is the area within the landscape boundary. The spatial extent of an investigation, from a statistical perspective, is the area defining the population we wish to sample. *Grain* is the size of the individual units of observation. A fine-grained map might represent information

as 0.1-ha units, whereas a map with an order of magnitude coarser resolution would have information structured into 1-ha units (Turner et al. 1989). Extent and grain define the upper and lower limits of resolution of a study, and inferences about scale-dependency are constrained by the extent and grain of the data (Wiens 1989a). One cannot extrapolate beyond the extent of the sampled population, nor can one infer pattern of objects smaller than the grain of the data.

It is critical that extent and grain be defined appropriately to represent the ecological phenomenon or organism under study, or there will be a good chance of reaching erroneous conclusions (McGarigal et al. in press). In practice, extent and grain are often dictated by the scale of the imagery (e.g., aerial photos, Landsat images) used or the technical capabilities of the computing environment. However, it is more ecologically meaningful to define scale from the perspective of the organism or ecological phenomenon under consideration (McGarigal et al. in press). Typically, however, one does not know the appropriate scale parameters. In such cases, it is advisable to choose a finer grain than is believed to be important because the grain sets the minimum resolution of investigation (McGarigal et al. in press). Once set, we can always resample to a coarser grain. In addition, one can specify the minimum patch size to be represented in a landscape, and this can easily be manipulated above the grain size. Indeed, it is often useful to reanalyze the same landscape using progressively coarser minimum patch sizes to better assess landscape heterogeneity across a range of scales (Thompson and McGarigal 2002).

There are often substantial practical implications of the choice of grain and extent. Many of the landscape metrics used to quantify landscape structure are highly sensitive to grain (McGarigal et al. in press). Metrics involving edge or perimeter will be affected, with edge lengths biased upwards in proportion to the grain size. Metrics based on cell adjacency information such as the contagion index of Li and Reynolds (1993) will be affected as well, because grain size effects the proportional distribution of adjacencies. In this case, as resolution is increased (grain size reduced), the proportional abundance of like adjacencies (cells of the same class) increases, and the measured contagion increases. Similarly, the measured degree of habitat fragmentation may vary with extent, especially if the habitat is not uniformly distributed throughout the entire study area (McGarigal et al. in press).

The ratio of grain to extent for a given landscape also warrants consideration. If the ratio is small (i.e., a coarse-grained map), then the landscape dynamics are likely to be dominated by boundary effects, analogous to the bias associated with small sample size in statistics (McGarigal et al. in press). Moreover truncation of patches artificially by the landscape boundary can have a dramatic influence on certain metrics. Also, if the landscape extent is small compared to the scale of the organism or ecological process under consideration then any metric will have questionable meaning. Metrics based on nearest neighbor distance or employing a search radius can be particularly misleading in such situations (McGarigal et al. in press).

Any model of landscape structure requires an explicit identification of scale. In any landscape structural analysis, it is incumbent upon the investigator or manager to select a scale (i.e., extent, grain, minimum mapping unit) that is appropriate to the phenomenon under consideration, as interpretation of landscape structure is

constrained scale. In addition, observed patterns or relationships should be evaluated relative to the limitations imposed by the scale of the data. In most applications a multi-scale assessment of habitat loss and fragmentation is recommended (McGarigal et al. in press), in which a relevant landscape model is established across a broad range of scales (i.e., grain and extent).

4 Defining the Relevant Spatiotemporal Context for Assessing Landscape Structure

4.1 Spatial Context

Each landscape has a context or regional setting, regardless of scale and how the landscape is defined. The importance of the landscape context is dependent on the phenomenon of interest, but typically varies as a function of the "openness" of the landscape (McGarigal et al. in press). The "openness" of the landscape depends not only on the phenomenon under consideration, but on the basis used for delineating the landscape boundary. For example, from a geomorphological or hydrological perspective, the watershed forms a natural landscape, and a landscape defined in this manner might be considered relatively "closed". Conversely, from the perspective of a bird population, topographic boundaries may have little ecological relevance, and the landscape defined on the basis of watershed boundaries might be considered a relatively "open" system. Local bird abundance patterns may be produced not only by local processes or events operating within the designated landscape, but also by the dynamics of regional populations or events elsewhere in the species' range (Wiens 1981, 1989b; Vaisanen et al. 1986; Haila et al. 1987; Ricklefs 1987).

Fragmentation metrics quantify the amount and configuration of habitat within the designated landscape boundary only. Consequently, the interpretation of these metrics and their ecological significance requires an acute awareness of the landscape context and the openness of the landscape relative to the extent of the landscape and the issues under consideration (McGarigal et al. in press). In particular, a focal habitat may be quite rare and fragmented in distribution at one landscape extent, but form a highly connected matrix at a broader or finer extent. Moreover, the ecological consequences of the measured habitat fragmentation may vary depending on the landscape extent in relation to the character of the landscape context. For example, a fragmented habitat distribution at one scale nested within a regional landscape context in which that habitat is abundant and highly connected may function differently than if that habitat is similarly rare and fragmented within the regional context as well (e.g., McGarigal and McComb 1995). Likewise, an abundant and unfragmented habitat distribution at the focal scale may not function as expected if the habitat is rare and highly fragmented within the broader context. Hence, any assessment of habitat loss and fragmentation should include at least a qualitative assessment of habitat conditions within the broader regional context.

4.2 Temporal Context

Fragmentation metrics quantify the pattern of habitat at a snapshot in time. Yet it is often difficult, if not impossible, to determine the ecological significance of the computed value without understanding the range of natural variation in habitat pattern. For example, in disturbance-dominated landscapes, habitat patterns may fluctuate widely over time in response to the interplay between disturbance and succession processes (e.g., Wallin et al. 1996; He and Mladenoff 1999; Haydon et al. 2000; Wimberly et al. 2000; McGarigal et al. 2001). It is logical, therefore, that landscape metrics should exhibit statistical distributions that reflect the natural spatial and temporal dynamics of the landscape. By comparison to this distribution, a more meaningful interpretation can be assigned to any computed value. Despite widespread recognition that landscapes are dynamic, there are few studies quantifying the range of natural variation in landscape pattern metrics (Neel et al. 2004). This remains one of the greatest challenges confronting landscape pattern analysis.

5 Choosing Metrics of Landscape Structure

Clearly, given the number and variety of components of landscape structure affected by habitat loss and fragmentation, it is unreasonable to expect a single metric, or even a few metrics, to be sufficient (Cushman et al. submitted). Therefore, a truly multivariate approach is warranted in most applications. Unfortunately, the selection of a suite of fragmentation metrics is constrained by the lack of a proper theoretical understanding of metric behavior. The proper interpretation of a landscape metric is contingent upon having an adequate understanding of how it responds to variation in landscape patterns (e.g., Gustafson and Parker 1992; Hargis et al. 1998; Jaeger 2000; Neel et al. 2004). Failure to understand the theoretical behavior of the metric can lead to erroneous interpretations (e.g., Jaeger 2000). Neutral models (Gardner et al. 1987; Gardner and O'Neill 1991; With 1997) provide an excellent way to examine metric behavior under controlled conditions because they control the process generating the pattern, allowing unconfounded links between variation in pattern and the behavior of the index (Gustafson 1998). Unfortunately, neutral models of fragmentation under various forms of fragmentation (e.g., random, contagious, disperse, corridor, edge, and nuclear) have not been used in a comprehensive manner to evaluate a broad array of metrics. Therefore, it is not possible to reliably identify the "best" measures of habitat loss and fragmentation. Rather, the measures described below provide a comprehensive, yet parsimonious, suite of metrics for quantifying habitat loss and fragmentation, and are recommended until such time as a more thorough investigation of metric behavior is completed.

There are five major spatial components to habitat loss and fragmentation: (1) habitat extent, (2) habitat subdivision, (3) patch geometry, (4) habitat isolation, and (5) habitat connectedness (McGarigal et al. in press). Numerous landscape metrics have been developed for each of these components (e.g., Baker and Cai 1992; McGarigal and Marks 1995; Jaeger 2000; McGarigal et al. 2002). However,

these categories are not discrete and many landscape metrics measure properties that relate to several components. Thus, a simple classification of metrics into these categories is not straightforward. Nevertheless, this classification has practical utility because it ensures that a comprehensive suite of metrics is selected. In the sections below, we identify and describe a parsimonious suite of metrics for measuring habitat loss and fragmentation (Table 1). It is important to note that the specific metrics included here do not represent a comprehensive list of useful fragmentation metrics and do not necessarily include the "best" metrics as considered from any one perspective. Rather, given the overwhelming number and variety of available metrics, it was our intent to suggest a parsimonious suite of metrics that measure different aspects of habitat loss and fragmentation and that when taken together may provide a comprehensive assessment of habitat loss and fragmentation in most applications.

5.1 Habitat Extent

Habitat extent represents the total areal coverage of the target habitat in the landscape and is a simple measure of landscape composition, represented by the following metric:

Percentage of Landscape. A straightforward and intuitive metric that measures habitat extent in relative terms is the *percentage of the landscape* (PLAND) comprised of the target habitat, defined as follows:

$$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \cdot 100$$

where P_i equals the proportion of the landscape occupied by the ith patch type (the focal habitat); a_{ij} is the area (m^2) of the jth patch; and A is the total landscape area (m^2). PLAND approaches 0 when the corresponding patch type (class) becomes increasingly rare in the landscape. PLAND equals 100 when the entire landscape is comprised of the focal patch type; that is, when the entire image is comprised of a single patch. PLAND is a relative measure, as opposed to total class area, and

Table 1 Proposed parsimonious suite of metrics for measuring habitat loss and fragmentation

Spatial component	Metric name	Acronym in FRAGSTATS
Habitat Extent	Percentage of Landscape	PLAND
Habitat Subdivision	Patch Density	PD
	Clumpy	CLUMPY
	Landscape Division	DIVISION
Patch Geometry	Total Core Area Index	TCAI
Habitat Isolation	Class-level Similarity Index	SIMILAR_AM
Habitat Connectedness	Correlation Length	GYRATE_AM

therefore may be used for comparing among landscapes of varying sizes. PLAND is not affected in any way by the spatial distribution or configuration of habitat patches.

5.2 *Habitat Subdivision*

Habitat subdivision deals explicitly with the degree to which the habitat has been broken up into separate patches (i.e., fragments), *not* the size, shape, relative location, or spatial arrangement of those patches. Because these latter attributes are usually affected by subdivision, it is difficult to isolate subdivision as an independent component. Subdivision can be measured in a variety of ways, but it is perhaps best defined by the absolute or relative number of patches, the degree of habitat aggregation or clumpiness, and the degree of subdivision derived from a geometric view based on the cumulative distribution of patch sizes, as represented by the following metrics:

Number of Patches or Patch Density. A simple and direct measure of habitat subdivision is given by the *number of patches* (NP) or, alternatively, *patch density* (PD). Unfortunately, both of these measures are difficult to interpret by themselves without also considering habitat area. Nevertheless, regardless of habitat area, as the number of habitat patches increases, technically the habitat becomes more fragmented (subdivided into disjunct patches). For this reason, this metric is often reported as a basic descriptor of habitat subdivision. The choice between NP or PD largely depends on the application. If more than one landscape is involved and they are different sizes, then PD is the more logical formulation because patch number is standardized to a per unit area. However, if a single landscape or multiple landscapes of equal extent are involved, the two formulations are equivalent and the choice becomes one of personal preference.

Clumpiness. A useful measure of habitat subdivision is given by the *clumpiness index* (CLUMPY) which measures the degree to which the focal habitat is aggregated or clumped given its total area. CLUMPY is calculated from the adjacency matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side-by-side on the map. CLUMPY is scaled to account for the fact that the proportion of like adjacencies (G_i) will equal P_i for a completely random distribution (Gardner and O'Neill 1991), and is defined as follows:

$$CLUMPY = \frac{G_i - P_i}{P_i} \quad for \quad G_i < P_i \& P_i < .5, \quad else \quad \frac{G_i - P_i}{1 - P_i}$$

$$\text{with} \quad G_i = \left(\frac{g_{ij}}{\sum_{i=1}^{n} g_{ik} - \min e_i} \right)$$

and where g_{ii} is the number of like adjacencies (joins) between pixels of patch type (class) i, g_{ik} is the number of adjacencies (joins) between pixels of patch types

(classes) i and k; min e_i is the minimum perimeter (in number of cell surfaces) of patch type (class) i for a maximally clumped class, and P_i is the proportion of the landscape occupied by patch type (class) i.

The formula is contingent upon G_i and P_i because the minimum value of G_i has two forms which depend on P_i. Specifically, when $P_i \leq 0.5$, $G_i = 0$ when the class is maximally disaggregated (i.e., subdivided into one cell patches) and approaches 1 when the class is maximally clumped. However, when $P_i \geq 0.5$, $G_i = 2P_i - 1$ when the class is maximally disaggregated and approaches 1 when the class is maximally clumped. Given any P_i, CLUMPY equals -1 when the focal patch type is maximally disaggregated; CLUMPY equals 0 when the focal patch type is distributed randomly, and approaches 1 when the patch type is maximally aggregated. Thus, CLUMPY has a straightforward and intuitive interpretation that indicates whether the focal habitat is more or less clumped than expected by chance alone. Note, because CLUMPY is based on "cell" adjacencies, it is sensitive to the grain size or resolution of the landscape. As the grain size is reduced (i.e., the landscape is mapped at a finer resolution), the proportion of like adjacencies will increase and the landscape will appear to be more clumped. Thus, this metric, like most others, must be interpreted in reference to the resolution of the map and is perhaps best used as a comparative index for comparing among different landscapes or the same landscape over time.

Degree of Landscape Division. Jaeger (2000) presented a new suite of indices that measure habitat subdivision from a geometric point of view and are calculated from the cumulative distribution function of the habitat patch sizes. *Degree of landscape division* (DIVISION) equals the probability that two randomly chosen places in the landscape under investigation are not situated in the same contiguous habitat patch. Thus, as the habitat becomes increasingly subdivided into smaller patches, the probability increases that two randomly chosen locations will belong to separate patches. DIVISION is defined as follows:

$$DIVISION = \left(1 - \sum_{j=1}^{n} \left\{\frac{a_{ij}}{A}\right\}^2\right) \cdot 100$$

where a_{ij} is the area (m^2) of patch ij and A is the total landscape area (m^2). DIVISION equals 0 when the landscape consists of a single patch, and approaches 100 as the proportion of the landscape comprised of the focal patch type decreases and as those patches decrease in size. DIVISION is maximum when the focal patch type consists of single one-cell patches. Conceptually, DIVISION and its related metrics (the splitting index and effective mesh size, not described here) are similar to simple measures of number of patches and average patch size, but they posses desirable mathematical properties that make them superior to the simpler measures. In particular, they have low sensitivity to very small patches, behave monotonically to the various fragmentation phases, and are sensitive to structural differences in the landscape mosaic (Jaeger 2000). DIVISION is closely related and effectively redundant with the area-weighted mean size of focal habitat patches, which explains its insensitivity to very small patches

(i.e., small patches are given very little weight). Note, unlike CLUMPY, DIVISION (at the class level) is effected by both habitat extent and subdivision, thus confounding these two components. Consequently, this metric must be interpreted in conjunction with PLAND and is perhaps best used as a comparative index for comparing among different landscapes with the same habitat extent.

5.3 *Patch Geometry*

Patch geometry deals explicitly with the spatial character of habitat patches. Given the myriad aspects of patch geometry, there exists a wide variety of patch geometry metrics. Here we focus exclusively on "core area" because it integrates several aspects of patch geometry relevant to habitat fragmentation. Core area is defined as the area within a patch beyond some specified depth-of-edge effect distance. Holding patch area constant, as a patch becomes more convoluted and complex in shape, core area decreases because less of the patch is greater than the specified depth-of-edge distance from the perimeter. Core area measures are particularly sensitive to habitat subdivision because, as just noted, they are sensitive to basic perimeter-area relationships. For example, holding the total area of habitat constant, the subdivision of habitat automatically decreases core area because of the increase in the ratio of habitat perimeter to area. Concomitant habitat loss and subdivision results in an even greater decrease in core area. Although there are many alternative ways to index core area, they all measure the same basic integrated aspect of patch geometry and are therefore largely redundant. Consequently, a single metric is sufficient, as follows:

Core Area Index. The *core area index* (CAI) is basically an edge-to-interior ratio like many shape indices (McGarigal et al. 2002), the main difference being that the core area index treats edge as an area of varying width and not as a line (perimeter) around each patch. CAI is computed at the patch level, as follows:

$$CAI = \frac{a_{ij}^{c}}{a_{ij}} \cdot 100$$

where a_{ij}^{c} is the core area (m^2) of patch ij based on specified depth-of-edge distances (m), and a_{ij} is the area (m^2) of patch ij. In other words, CAI equals the percentage of a patch that is core area. CAI can be averaged across all patches of the focal habitat (weighted by patch area) to provide a suitable class-level metric, or an equivalent *total core area index* (TCAI) can be calculated directly, as follows:

$$TCAI = \frac{\sum_{j=1}^{n} a_{ij}^{c}}{\sum_{j=1}^{n} a_{ij}} \cdot 100$$

TCAI is equivalent to the *area-weighted mean core area index* (CAI_AM) reported in FRAGSTATS (McGarigal et al. 2002). TCAI equals 0 when there is no core area

(i.e., every location within the focal habitat is within the specified edge influence distance from the habitat edge); that is, when the habitat contains no core area. TCAI approaches 100 when the habitat, because of patch size, shape, and edge width, contains mostly core area. TCAI is a relative index; it does not reflect patch size, class area, or total landscape area; it merely quantifies the percentage of available area, regardless of whether it is 10 ha or 1,000 ha, comprised of core. Consequently, this index does not confound area and configuration; rather, it isolates the configuration effect. For this reason, the core area index is probably best interpreted in conjunction with total habitat area, or its relativized equivalent – PLAND.

5.4 Habitat Isolation

Habitat isolation deals explicitly with the spatial and temporal *context* of habitat patches, rather than the spatial character of the patches themselves. Unfortunately, isolation is a difficult thing to capture in a single measure because there are many ways to quantify context. Isolation can be measured in the spatial dimension in several ways, depending on how one views the concept of isolation. Here, we focus exclusively on a measure of neighborhood similarity, or, conversely, contrast, within a specified ecological neighborhood surrounding each habitat patch. Isolation is measured by the degree of contrast (i.e., the magnitude of differences in one or more attributes between adjacent patch types) between the focal habitat and neighboring patches.

Similarity Index. The *similarity index* (SIMILAR) is a patch-level measure of neighborhood similarity (McGarigal et al. 2002). It considers the size and proximity of all patches, regardless of class, whose edges are within a specified search radius of the focal patch. SIMILAR is computed at the patch level, as follows:

$$SIMILAR = s_{ij} = \sum_{k=1}^{n} \frac{a_{ijs} \cdot d_{ik}}{h_{ijk}^2}$$

where a_{ijs} is the area (m^2) of patch ijs within the specified neighborhood (m) of the focal patch; d_{ik} is the similarity (coefficient between 0–1) between the focal patch (type i) and the kth patch within the specified neighborhood; and h_{ijs} is the distance (m) between the focal patch and each neighboring patch ijs, based on patch edge-to-edge distance. SIMILAR can be averaged across all patches of the focal class (weighted by patch area) to provide a suitable class-level metric, as follows:

$$SIMILAR\_AM = \sum_{j=1}^{n} \left[s_{ij} \left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \right) \right]$$

SIMILAR_AM equals 0 if all the patches surrounding the focal habitat patches have a zero similarity coefficient (i.e., maximum contrast). SIMILAR_AM increases as the habitat patches are increasingly surrounded by patches with greater similarity coefficients and as those similar patches become closer and more contiguous in distribution. The similarity index quantifies the spatial context of a (habitat) patch in relation to its neighbors of the same or similar class; specifically, the index distinguishes sparse distributions of small and insular habitat patches from configurations where the habitat forms a complex cluster of larger, hospitable (i.e., similar) patches. Note, in a binary landscape consisting of the focal habitat class and a non-habitat matrix, as might be represented under an island biogeographic perspective on landscape structure, the similarity index reduces to the proximity index given in FRAGSTATS [see also Gustafson and Parker (1992) and Whitcomb et al. (1981)], which considers only patches of the focal class. Note, the similarity index must be interpreted carefully in relation to habitat extent. Specifically, because it is computed at the patch level and considers only the composition of the landscape surrounding each habitat patch, not the area of the patch itself, it can exhibit erroneous behavior under certain circumstances. For example, when the focal habitat comprises most (or all) of the landscape and is connected into a single matrix-forming patch, SIMILAR_AM equals 0 because there are no other (similar) habitat patches in the neighborhood, implying isolation when in fact the habitat is both abundant and highly connected. Thus, SIMILAR_AM is best interpreted in conjunction with PLAND and its use should probably be limited to landscapes in which the focal habitat is not matrix forming (i.e., typically say PLAND < 30–40%) and consists of multiple patches.

5.5 *Connectedness*

Connectedness integrates all of the above components and involves both a structural component (continuity) and a functional component (connectivity). As noted previously, it is difficult to isolate connectedness in a metric owing to the myriad constituent components. Consequently, the range of available connectedness metrics is somewhat limited; although, this is an area of active development in landscape pattern analysis so new measures will likely become available in the future. Here we focus on a single continuity metric and a single connectivity metric. Note, however, that there is considerable redundancy between these metrics and the suggested isolation and subdivision metrics.

Correlation length. A useful measure of the continuity or structural connectedness of habitat is the *correlation length index* (CLI) (Keitt et al. 1997), which is derived from the patch *radius of gyration* (GYRATE), as follows:

$$GYRATE = g_{ij} = \sum_{r=1}^{z} \frac{h_{ijr}}{z}$$

where h_{ijr} is the distance (m) between cell *ijr* [located within patch *ij*] and the centroid of patch *ij* (the average location), based on cell center-to-cell center distance; and z is the number of cells in patch *ij*. GYRATE equals the mean distance (m) between each cell in the patch and the patch centroid and represents the average distance an organism can move and stay within the patch boundary. The correlation length index (CLI) is computed as the *area-weighted average patch radius of gyration* (GYRATE_AM), as follows:

$$CLI = GYRATE\_AM = \sum_{j=1}^{n} \left[g_{ij} \left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \right) \right]$$

where a_{ij} is the area of patch *ij*. CLI equals 0 when the habitat consists of single-cell patches and increases as the patches increase in extensiveness. Correlation length is intuitively appealing, because as patches become smaller and more compact, they extend over less space and therefore provide for less physical continuity of the habitat across the landscape. Large and elongated patches extend over greater space and provide for greater connectedness of the habitat. Thus, holding habitat area constant, as the habitat becomes more subdivided during fragmentation, correlation length decreases. Correlation length can be interpreted as the average distance an organism might traverse the map, on average, from a random starting point and moving in a random direction, i.e., it is the expected traversibility of the map (Keitt et al. 1997).

Traversibility Index. A useful measure of the functional connectivity of habitat is given by the *traversibility index* (TRAVERSE) based on the idea of ecological resistance (McGarigal et al. 2002). The premise is that a hypothetical organism dispersing from a focal habitat cell in a highly traversable neighborhood can reach a large area with minimal crossing of "hostile" cells. This metric uses a resistance surface to determine the area that can be reached from each cell in the focal habitat. The focal cell gets an organism-specific "bank account," which represents, say, an energy budget available to the organism for dispersal from the focal cell. The size of the account is selected to reflect the organism's dispersal or movement ability. Each patch type (including the focal patch type) is assigned a cost based on a user-specified resistance matrix. Specifically, relative to a each focal patch type, each patch type is assigned a resistance coefficient in the form of weights ranging from 1 (minimum resistance, usually associated with the focal patch type) to any higher number that reflects the relative increase in resistance associated with each patch type. The metric is computed by simulating movement away from the focal cell in all directions, where there is a cost to move through every cell. Under the best circumstances (i.e., minimum resistance), there will exist a maximum dispersal area based on the specified account or energy budget. Note that assigning a (small) cost for traveling through the focal community (typically a cost of 1) results in a linearly decaying function. Moving through more resistant cells costs more and drains the account faster. Thus, depending on the resistance of the actual landscape

in the vicinity of the focal cell, there will be a certain area that a dispersing organism can access. This area represents the least-cost hull around the focal cell, or the maximum distance that can be moved from the cell in all directions until the "bank account" is depleted. This dispersal area, given as a percentage of the maximum dispersal area under conditions of minimum resistance, provides a measure of the relative traversability of the landscape in the vicinity of the focal cell. Averaging this index across cells of the focal habitat provides a class-level index of traversability, computed as follows.

$$TRAVERSE = \frac{\left(\sum_{r=1}^{z} t_{ir} \Big/ z_i\right)}{t_{\max}} \cdot 100$$

where t_{ijr} is the least cost hull area around the rth cell in the focal patch type (i); z_i is the total number of cells in the focal patch type (i); and $t_{\max}$ is the maximum least cost hull area around a cell of the focal patch type (i) given minimum resistance. TRAVERSE equals 0 when the focal habitat consists of one or more single-cell patches surrounded by hostile patch types that prevent any movement (i.e., function as barriers). This is achieved when the resistance coefficient for the neighboring patch type(s) is greater than the user-specified bank account for the focal cell. TRAVERSE equals 100 when the focal habitat is surrounded by minimally resistant patch types. TRAVERSE is computed at the cell level and then averaged across cells in the focal patch. As a result, this metric requires substantial computations and may take considerable time to compute for a large landscape. In addition, this metric requires the user to specify an appropriate resistance matrix containing coefficients for each pairwise combination of patch types, as well as a scaling factor that governs the size of the maximum least cost hull; that is, the size of the area surrounding the focal cell that is accessible given minimum resistance.

6 Landscape Trajectory Analysis

Once the model of landscape structure, the appropriate spatial scales, and spatio-temporal reference framework have been determined it is possible to meaningfully evaluate the current condition of the landscape in terms of the area and configuration of landscape elements. To evaluate the meaning of these conditions it is essential to have a quantitative goal or benchmark with which to compare. Specifically, it is desirable to compare current conditions to a desired condition which expresses the actualization of the management objectives. Importantly, for these desired landscape conditions to be meaningful in evaluating current conditions they must be expressed in terms of quantitative values and ranges for a selection of landscape metrics. Once desired conditions are thus expressed it is possible to evaluate the current condition in terms of its departure from desired conditions. Cushman and McGarigal (2006) present the analytical framework for evaluating landscape structure with respect to

past conditions or desired future conditions. The framework is based on several key ideas, including (a) quantifying the multivariate character of landscape structure; (b) evaluating current conditions with respect to historic ranges or desired future conditions; (c) measuring changes in landscape structure over time; and (d) quantitatively comparing the rates and patterns of landscape change among mulitple landscapes over time.

6.1 Landscape Structure Space

Landscape structure space is derived from a p-dimensional space, where each dimension represents a different landscape metric. We refer to this p-dimensional space as *landscape metric space*, denoting that the dimensions are defined by the individual landscape metrics (but in standardized form). Because many landscape metrics are partly redundant (Riitters et al. 1995) it is often preferable to obtain orthogonal combinations from an unconstrained ordination technique (McGarigal et al. 2000), such as principal components analysis (PCA) (e.g., McGarigal and McComb 1995; Cushman and Wallin 2000) or nonmetric multidimensional scaling (NMDS). In this manner, the p-dimensional space is reduced to an m-dimensional space, where hopefully $m << p$. We refer to this reduced m-dimensional space as *landscape structure space*, denoting that the dimensions now represent composite structure gradients whose exact definitions will vary among data sets depending on the suite of landscape metrics measured and idiosyncracies of the specific landscapes. Representing multivariate measurement of landscape structure as an m-dimensional landscape structure space greatly facilitates analysis when multiple metrics are measured simultaneously. The challenge of describing each landscape across all measured metrics is replaced by describing the relative locations and rates and directions of change in a much reduced landscape structure space. This makes for much more concise and meaningful analysis. Note, however, that the trajectory analysis described below can just as easily be conducted on the original p-dimensional landscape metric space, although the solution is not as concise. Ultimately, the choice of approach depends on how successfully the variance structure of the measured landscape metrics can be summarized by ordination. In the description that follows, we will presume the use of an ordination approach.

6.2 Location and Distance

The location of a landscape in structure space is defined by the coordinates of the landscape on each axis of the landscape structure space. These coordinates are simply the values of the orthogonal axis scores (e.g. from PCA or NMDS). Location is defined by the position vector describing the direction and distance of the landscape from the origin of the structure space. In simplest terms, the position vector describes the location of the landscape in the m-dimensional structure space. The

position vector is most easily handled in component form, which decomposes its components along each axis of the structure space:

$$r_i = x_{i1} + x_{i2} + \ldots + x_{im}$$

The coefficients x_{im} are the scalar elements of the position vector, defining the magnitude of displacement of the ith landscape (r_i) from the origin along each of the m dimensions of the structure space.

To evaluate the current landscape condition it is essential to quantitatively calculate the distance of the landscape from a reference or desired condition in landscape structure space. This distance is defined as the Euclidean distance between the location of the landscape and the reference or desired condition:

$$\overline{d}_i = \sqrt{\sum_{k=1}^{m} (X_{ijk} - X_0)^2}$$

where x_{ijk} is the score for landscape i $(1 \ldots \mathrm{n})$ at time j $(0,\ t)$ on axis k $(1 \ldots \mathrm{m})$. This is simply the Pythagorean theorem applied to m dimensions. Displacement in m dimensions of the current from the reference or desired condition provides a measurement of how much the overall landscape structure departs from management objectives. Alternatively, displacement can also be expressed in component form:

$$\overline{d}_i = \Delta x_{i1} + \Delta x_{i2} + \ldots + \Delta x_{im}$$

where Δx_{ik} is the difference in scores between time $j = t$ and 0 for landscape i $(1 \ldots \mathrm{n})$ on axis k $(1 \ldots \mathrm{m})$. In this form, displacement is defined as the change in the landscape structure space along each dimension. This form facilitates interpretation because displacement can be described directly in relation to the particular aspects of landscape structure represented by each dimension.

6.3 *Landscape Trajectories*

Evaluating current conditions with respect to reference and desired conditions provides a measure of departure to guide management. However, it is insufficient to fully inform management decisions as to what management strategy will most effectively lead to the creation of the desired conditions on the landscape of interest. Dynamic landscape simulation models are useful in this task (Cushman and McGarigal 2006). By explicitly simulating future landscape conditions under alternative management regimes, involving different areas, frequencies and patterns of treatment or restoration, it is possible to create plausible futured landscapes. The concepts of location and distance in landscape structure space can then be used to determine which management alternatives most efficiently lead to creation of desired landscape condition (Cushman and McGarigal 2006). Specifically, multiple

plausible alternative scenarios should be simulated. As landscape dynamics simulation models are stochastic it is important to produce a sample of replicate runs on each scenario (usually 100–500), and to output results at a temporal time-step sufficiently fine to match the temporal scale of the management and disturbance processes and to be relevant to management decision making (usually 1–10 years).

Once these simulations have been run it is relatively simple to calculate the mean and variability of landscape structure in each scenario at each time step. Then it is straightforward to compare management alternatives in terms of the degree and rate to which they lead to changes from current landscape structure to desired landscape structure (Cushman and McGarigal 2006). In this comparison, calculation of distance from initial condition and from desired condition at each time step is very useful, as are calculations of divergence among scenarios and velocity of change, in total, and the component of velocity toward or away from desired conditions (Cushman and McGarigal 2006). Divergence is defined as the Euclidean distance between the location of different landscapes at the same point in time:

$$\overline{g}_j = \sqrt{\sum_{k=1}^{m} (X_{ajk} - X_{bjk})^2}$$

where x_{ijk} is the score for landscape i (a,b) at time j $(0 \ldots t)$ on axis k $(1 \ldots m)$. Like displacement, this is simply the Pythagorean theorem applied to m dimensions, the difference being that here the distance is between two different trajectories at the same point in time, instead of the distance a single trajectory has moved away from the starting point after any time period.

Velocity is a measure of both the rate and direction of change in the landscape trajectory:

$$\overline{v}_i = \Delta r_i / \Delta t$$

where Δr_i is the change in position vector for the ith landscape and Δt is the interval under consideration. Velocity can described as the rate and direction of movement between two points in m-dimensional landscape structure space. Velocity can also be expressed in component form:

$$\overline{v}_i = (\Delta x_{i1} + \Delta x_{i2} + \ldots + \Delta x_{im})/\Delta t$$

where Δx_{ik} is the difference in scores for landscape i $(1 \ldots n)$ on axis k $(1 \ldots m)$ for that interval. In this form, velocity is defined as the rate of change along each dimension of the landscape structure space.

Trajectory analysis allows quantitative assessment of current landscape structure with respect to desired conditions, by calculating the *distance* in structure space between current and desired conditions. It also allows assessment of the

displacement, divergence, velocity and acceleration of landscape change under alternative scenarios. Comparing the *displacement* of each scenario from initial conditions over time provided a means to evaluate the nature and extent of change from the original state. Computing the *divergence* among scenarios over time provided an objective measure of the relative differences among scenarios in their impacts on marten habitat area and fragmentation. Between displacement and divergence in landscape structure space we have the means to quantify the impact of scenarios both with respect to initial conditions and relative to each other. These are the two comparisons most needed by landscape managers to provide information on the effects land management alternatives. Also, quantifying *velocity* and *acceleration* through landscape structure space provides rigorous description of the rates and directions of changes in landscape structure. These measures facilitate quantitative comparison among scenarios and allow a quantitative comparison of which alternative management scenarios most effectively and rapidly lead to achieving the desired future landscape condition.

Landscape trajectory analysis is also the appropriate tool to monitor changes as management occurs. Simulation models produce expected results, but the results of such models must be treated as spatial hypotheses that must be verified and tracked. Thus, the key final component in landscape analysis is monitoring changes in landscape structure as they occur, comparing them to expectations from simulation models, and with movement toward or away from desired conditions. Using measures of *distance, divergence, displacement, velocity* and *acceleration* managers can monitor the changes in landscape patterns as they occur in a quantitative framework that allows direct comparison to desired conditions, and allows for evaluation of effectiveness of the current management approach. This is essential to provide the critical feedback needed to guide adaptive landscape management.

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