Ecological Indicators 5 (2005) 273–279

ECOLOGICAL INDICATORS

This article is also available online at:
www.elsevier.com/locate/ecolind

Downscaling indicators of forest habitat structure from national assessments

Kurt H. Riitters *

Southern Research Station, US Forest Service, 3041 Cornwallis Road, Research Triangle Park, NC 27709, USA

Accepted 1 April 2005

Abstract

Downscaling is an important problem because consistent large-area assessments of forest habitat structure, while feasible, are only feasible when using relatively coarse data and indicators. Techniques are needed to enable more detailed and local interpretations of the national statistics. Using the results of national assessments from land-cover maps, this paper demonstrates downscaling in the spatial domain, and in the domain of the habitat model. A moving window device was used to measure structure (habitat amount and connectivity), and those indicators were then analyzed and combined with other information in various ways to illustrate downscaling.
Published by Elsevier Ltd.

Keywords: Biodiversity; Habitat; Scale; Spatial analysis; Spatial pattern

1. Introduction

Suitable habitat structure (i.e., amount and spatial pattern) is essential for maintenance of forest biodiversity. Furthermore, consistent measurements of structure indicators over large areas are essential for national and international assessments. Upscaling from local information has not been feasible in many large-area assessments because there is no information for some places, or for many species, and because detailed habitat maps are not thematically or cartographically comparable from place to place.

Consistency in recent U.S. national assessments has only been achieved by using simpler definitions of habitat that can be measured on land-cover maps derived from satellite imagery (Heilman et al., 2002; Riitters et al., 2002, 2004). However, the resulting picture of habitat structure lacks detail, and cannot by itself resolve many specific questions such as the habitat status for a particular species. Since achieving measurement consistency at some level of detail is better than having no national assessment at all, this focuses attention on downscaling the information so that it can be interpreted in light of local circumstances. With a view towards encouraging broader application of available statistics, this paper summarizes some approaches and limitations to downscaling national indicators of habitat structure.

* Tel.: +1 919 549 4015; fax: +1 919 549 4047.
E-mail address: kriitters@fs.fed.us.

1470-160X/$ – see front matter. Published by Elsevier Ltd.
doi:10.1016/j.ecolind.2005.04.003

2. Methods

In the examples that follow, the National Land Cover Data (NLCD) land-cover map represents habitat. The NLCD used Landsat Thematic Mapper (TM) data (circa 1992) to map 21 classes of land cover at a spatial resolution of 0.09 ha pixel^{-1} for the conterminous U.S. (Vogelmann et al., 2001). The four NLCD forest classes were combined into one forest class, yielding a binary map of forest (''habitat'') and non-forest (Riitters et al., 2002). There are $\sim 8.6 \times 10^9$ pixels of all land-cover types on the NLCD map, of which $\sim 2.8 \times 10^9$ are forest pixels. Since each ''edge'' between adjacent pixels is nominally 30 m long, the NLCD potentially resolves $\sim 5 \times 10^8$ km of edge.

After Fahrig (1997), two measurements were used to characterize habitat structure in terms of its amount and spatial pattern within a fixed-area support region. Habitat amount was measured by percent forest (P_f), defined as the proportion of pixels in the support region that are forest. Habitat spatial pattern was measured by the pixel-to-pixel connectivity of forest (P_{ff}), defined as the probability that a pixel adjacent to a forest pixel is also forest (Riitters et al., 2000). Connectivity is estimated from the attribute adjacency table (Musick and Grover, 1991) which in this case enumerates the {forest, forest} and {forest, non-forest} adjacent pixel pairs in the support region as follows:

$$P_{ff} = \frac{a}{a+b} \qquad (1)$$

where a is the number of {forest, forest} pixel pairs and b is the number of {forest, non-forest}pixel pairs.

A moving window device was used to measure P_f and P_{ff} on the habitat map. Moving windows are commonly used in landscape ecology for purposes such as edge detection (Fortin, 1994), spectral analysis (Keitt, 2000), and fractal analysis (Milne, 1991; Plotnick et al., 1993), and to obtain a ''field'' representation of habitat (Dale et al., 2002). A moving window operates by moving a fixed-area window over the map so as to place a support region around each pixel. Measurements are made at each placement of the window, and the values are assigned to the location of the pixel at the center of the support region. For present purposes, the process was repeated with square support regions of size 2.25 ha (5 pixel $\times$ 5 pixel), 7.29 ha (9 pixel $\times$ 9 pixel), 65.61 ha (27 pixel $\times$ 27 pixel), 590.49 ha (81 pixel $\times$ 81 pixel), and 5314.41 ha (243 pixel $\times$ 243 pixel) (Riitters et al., 2002).

An interpretive aid comes from the dualism of content versus context that is embodied in landscape characterization. On one hand, a subject landscape can be described by its contents, using indices calculated from the habitat objects that it contains. In that case, the indicators for a landscape represent all the habitat pixels in that landscape. On the other hand, each habitat pixel can be described by its context, using indices calculated from the habitat in the landscape that surrounds it. The indicators for the surrounding landscape then apply only to the center pixel. In the first instance, each landscape contains its own unique set of habitat pixels, and in the second, each habitat pixel exists in the context of its own unique set of (nested) landscapes. The moving window device gives measurements of context for each pixel, and the context interpretation is adopted here.

3. Scale terminology

The science of scale remains a central problem in landscape ecology (Wu and Hobbs, 2002). It is necessary to be explicit about the scales of the analysis, since upscaling or downscaling must involve a change in at least one aspect of scale. Following the terminology of Dungan et al. (2002), some aspects of scale are set by the data. The *extent* is the conterminous United States and the *grain of data* is either a pixel (when measuring P_f) or a boundary (''edge'') between two adjacent pixels (for P_{ff}). The *resolution* or map legend is originally 21 classes, and the *cartographic ratios* are determined by the size of a pixel (0.09 ha) and length of the boundary between pixels (30 m). Some other aspects of scale are set by the implementation of the moving window. The *support region* refers to a window shape and size. The *lag* distance between sampling units is one pixel since the window moves in steps of one pixel, and thus the *grain of the output* map is also one pixel. Finally, some aspects of scale are set in the domain of the habitat model. Individual species perceive habitat in different terms as well as at different scales (Wiens, 1989). Examples of scaling in the habitat model domain include choosing a specific habitat indicator, or setting a threshold value for an indicator.

The moving window leaves both the lag and the grain of data at their original, minimum values, which makes the most use of the available data and preserves the most options for aggregating results in different ways later on. Reducing the size of the support region is not downscaling because all sizes are tested for each pixel. Rather, different support region sizes are a way to sample habitat structure at different spatial frequencies; large regions are more sensitive to lower spatial frequency structure and vice versa (Riitters et al., 2000). Choosing a particular support region size based on home range size (Riitters et al., 1997) constitutes downscaling in the domain of the habitat model. This leaves extent, resolution, and the ‘‘habitat model’’ as candidates for downscaling, and these aspects of downscaling are discussed here.

4. Approaches to downscaling

Considering map extent, it is trivial to examine the indicator values at any particular location, or to summarize the values within an arbitrary map extent such as a watershed. Considering resolution, within the limits of the original map resolution it is also clearly feasible to perform the analysis with more specific definitions of habitat such as ‘‘deciduous forest’’ or ‘‘forest that is adjacent to grassland’’. For the P_{ff} indicator, another possibility is to partition the ‘‘non-connectivity’’ (i.e., the quantity $1 - P_{ff}$) into components representing different proximate causes of non-connectivity (Wade et al., 2003). To accomplish that, the attribute adjacency table is expanded so that the {forest, non-forest} edges can be resolved into more categories such as {forest, agriculture}, {forest, water}, and so forth.

Where local maps can provide more detailed thematic resolution, a geographic overlay of national and local maps permits interpretation with respect to local habitat types (Riitters et al., 2003). If only the locations of a particular local habitat are considered, then the national statistics are interpretable as (generalized) habitat structure in the vicinity of a (particular) habitat. This is not the same as the habitat structure of that particular habitat type, but in many cases the distinction is not very important (Riitters et al., 2000). Since the moving window device provides measurements for all pixels, whether or not they are habitat in the national analysis, either the local map or the national map can be used to identify the pixels to be included. Thus, it is possible to harmonize the stratification with respect to either local or national definitions of habitat, and still maintain comparability with national statistics.

The most opportunities for downscaling appear to be in the domain of the habitat model. To illustrate one approach, consider choosing a threshold P_f value based on the ‘‘habitat density’’ requirement for a particular species. Fig. 1 shows the proportion of all forest pixels in the eastern United States that meet the criteria of $P_f > 0.6$, >0.9, and 1.0. Less of the total habitat is suitable habitat as the criterion is made more restrictive, and as the criterion is applied over larger support region sizes. The interpretation is that species with lower habitat density requirements and smaller home range sizes find more suitable habitat than species with higher habitat density requirements and larger home range sizes. A threshold P_f value could also be selected based on movement requirements. In a landscape with no spatial pattern the appropriate threshold (from percolation theory) is approximately $P_f = 0.6$, but real landscapes always have pattern and invoking a threshold based on movement has to take actual spatial pattern into account (With et al., 1997), and the P_{ff} measurement could be used for that purpose (Riitters et al., 2000).

The same sort of analysis can be combined with downscaling in the spatial domain. Fig. 1 shows a

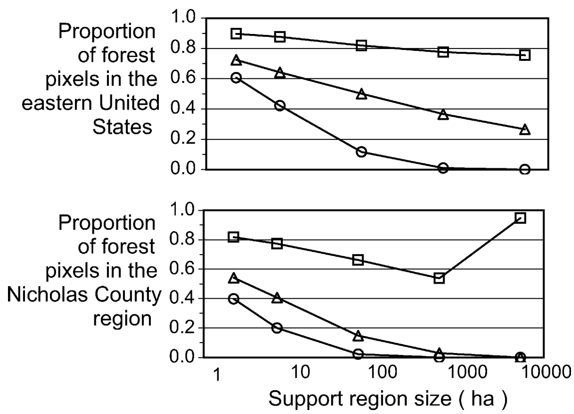

Fig. 1. The proportion of forest pixels in the eastern United States (top) and the Nicholas County region (bottom) that meet the criteria of $P_f > 0.6$ (□), $P_f > 0.9$ (△), and $P_f = 1.0$ (○).

summary of the same statistics for a ~5000 ha portion of Nicholas County (West Virginia). In comparison to the entire eastern United States, a lower proportion of the forest in this reduced extent is suitable habitat for all criteria and support sizes except one. The exception is for the lowest habitat density requirement ($P_f > 0.6$), for which species with a larger home range (support region) size may find more suitable habitat in Nicholas County than species with smaller home range sizes. The exception occurred because the study area contains a relatively low proportion of forest but is embedded in a larger area that contains a relatively high proportion of forest. The types of trends shown in Fig. 1 are usually monotonic for reasonably large extents (e.g., millions of hectares) and as a result, interpolation between support region sizes is justifiable. For smaller extents (e.g., thousands of hectares), departures from monotonic forms create the opportunity for very localized interpretations of structure but can only use the specific support region sizes employed in the analysis.

Downscaling in the domain of the habitat model can also involve looking at the indicators of habitat structure in different ways. Habitat for edge-sensitive species can be described in terms of "core" habitat that is a minimum distance from habitat edge (Heilman et al., 2002). In that regard, a threshold value of $P_f = 1.0$ is relevant because a forest pixel embedded in a completely forested support region is by definition more than a certain distance from the nearest forest edge, and the distance depends on support region size (Riitters et al., 2002). Estimates of suitable "core" habitat can be obtained by the proportion of forest pixels meeting the threshold for the appropriate support region size; the estimates are computationally equivalent to those obtained by a traditional buffer operation on patches of habitat.

The available information can also be combined to estimate other indicators. A measure of habitat perimeter–area ratio in a support region can be obtained from the amount of habitat and the attribute adjacency table, and the estimate is equivalent to weighted average perimeter–area ratio from a traditional patch-based approach. In another example, distinctions between types of habitat edge such as perforations in forest patches versus outer perimeters of patches can be quantified by classifying pixels in terms of the values of P_f and P_{ff} (Riitters et al., 2000).

In principle, the moving window device can measure any indicator, but in practice the amount and connectivity of habitat may be sufficient. Some indicators traditionally obtained from a patch-based approach (e.g., perimeter–area ratio, amount of core forest) can be recovered from a moving window analysis without explicitly identifying the patches. This raises the question of how many other patch-based measurements can be recovered from the analysis. One promising approach is based on Milne's (1992) observation that local pattern can be deduced by simultaneously considering the value of P_f for several support region sizes. Changes in P_f with increasing support region size imply changes in the distribution of forest at different spatial frequencies, but the specific nature of the changes have geometric interpretations.

Consider a cluster analysis of the forest pixels in Nicholas County. Using a centroid sorting algorithm, the forest pixels were grouped into eight clusters according to similarity of P_f values for the five support region sizes (Fig. 2). There was not much variation in average P_f among clusters for the largest support region size, indicating that size was not very influential in forming clusters. In clusters 1, 7, and 8, the average P_f for the other four sizes was roughly the same within clusters but different between clusters. Clusters 2 and 3 were similar in that the average value decreased with increasing support region size, but the larger decrease in cluster 3 distinguished it from cluster 2. Clusters 4 and 6 exhibited increases in P_f

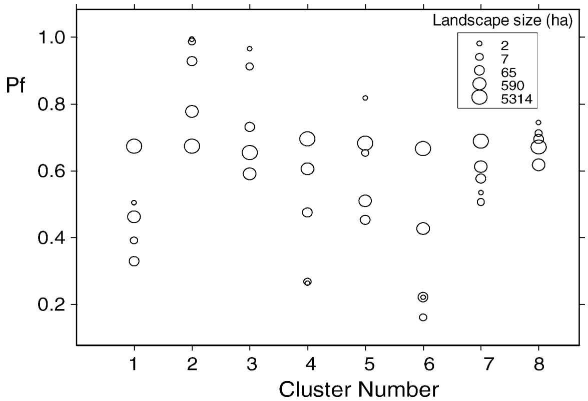

Fig. 2. Cluster means of the P_f indicator for five landscape (support region) sizes, for eight clusters identified through multivariate analysis of the Nicholas County example.

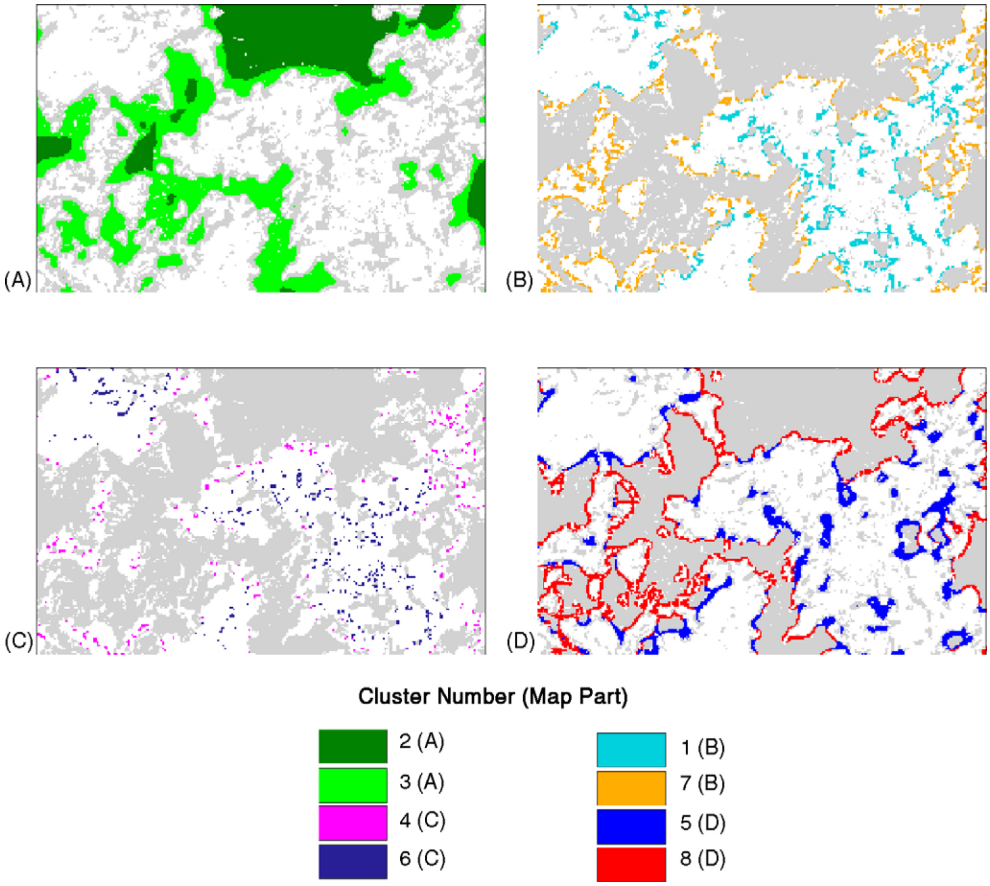

Fig. 3. Cluster maps for eight clusters identified in the Nicholas County example. The clusters are mapped two at a time in each of four map parts (A–D) to assist interpreting the type of context that is represented by each cluster. White represents non-forest pixels and gray represents forest pixels that are not in one of the two clusters for that map part.

with support region size, with a larger increase in cluster 4. Cluster 5 exhibited intermediate patterns.

Maps of the eight clusters (Fig. 3) make it easier to interpret the context of forest that is contained in each cluster. Clusters 2 and 3 represent forest near the interior of the largest forest patches, and cluster 2 is ‘‘more interior’’ than cluster 3. Forest pixels in clusters 4 and 6 are in the smallest patches, and the patches in cluster 4 are closer to large forest patches. The other four clusters represent forest near the edges of the larger forest patches. Clusters 1 and 5 represent ‘‘convex’’ edges (e.g., peninsulas) whereas clusters 7 and 8 represent ‘‘concave’’ edges with respect to other forest. These edges are further differentiated by a higher overall P_f in clusters 5 and 8, in comparison to clusters 1 and 7 (Fig. 2). While these indicators are not computationally equivalent to traditional indicators of patch size or juxtaposition, they are conceptually similar, and it may be worth reformulating the habitat model to take advantage of the new types of information that can be recovered without resorting to measuring scale-contingent objects like patches. Of course, it is also possible to estimate traditional patch-based indicators from maps of suitable habitat from a moving window analysis (Riitters et al., 1997).

5. Discussion

Single-scale approaches are of little use except for very specific frames of reference. Analyzing the scale-dependent nature of forest habitat is critical to supporting large-area biodiversity assessments that must address many frames of reference. The inherent difficulty of interpreting complex scaling relations suggests that measurement approaches should be intuitive, transparent, and as simple as possible. In comparison to classical indices that focus attention on scale-contingent objects like patches, simpler indices based on frequencies of mapped classes or of pixel edges between mapped classes might be better choices. As demonstrated here, a multiple-scale, moving window analysis of the amount and connectivity of forest is a deceptively simple approach that supports many types of inferences about habitat structure.

The landscape characterization dualism of content versus context is consistent with hierarchy theory (O'Neill et al., 1986) in the sense that context is a constraint or a boundary condition when downscaling. For example, the amount of habitat in 40-year-old Douglas-fir forests is necessarily less than the amount of habitat in all forest types together. The dualism exists at all scales and there is no preferred scale, and as a result, the present analysis could be evaluated in terms of how it relates to higher levels in the hierarchy. One can envision performing a similar analysis for all natural land-cover types together (e.g., modeling habitat as forest plus grassland plus shrubland), and then partitioning or downscaling those results to address habitat questions separately for each land-cover type.

National assessments will never provide as much detailed information as a local investigation. But it is not feasible to conduct detailed local investigations everywhere, which prevents building up comprehensive national assessments from the available studies. The practical tradeoff is the classical one between generality, precision, and realism (Levins, 1966). National analyses should be aimed primarily at maximizing generality and realism, whereas improving precision should be a local objective pursuant to specific frames of reference. The most community benefit will be realized from national data if it is flexible with respect to frame of reference. If local assessments can all use the same data, then the local results for different endpoints (e.g., habitat, aesthetics, water quality, etc.) can be more easily compared, and locations can be more easily compared with each other. Widespread use of common data will almost certainly make it easier to integrate results from a larger number of studies that, in turn, will lead to better national and global environmental assessments.

Acknowledgements

The Forest Health Monitoring Program and the SPRA Staff of the U.S. Forest Service provided funding for this research. Discussions with Theresa Evans and Samuel Lammie of the Monongahela National Forest stimulated investigation of the problem of downscaling national indicators.

References

Dale, M.R.T., Dixon, P., Fortin, M.-J., Legendre, P., Myers, D.E., Rosenberg, M.S., 2002. Conceptual and mathematical relationships among methods for spatial analysis. Ecography 25, 558–577.

Dungan, J.L., Perry, J.N., Dale, M.R.T., Legendre, P., Citron-Pousty, S., Fortin, M.-J., Jakomulska, A., Miriti, M., Rosenberg, M.S., 2002. A balanced view of scale in spatial statistical analysis. Ecography 25, 626–640.

Fahrig, L., 1997. Relative effects of habitat loss and fragmentation on population extinction. J. Wildlife Manage. 61, 603–610.

Fortin, M.-J., 1994. Edge detection algorithms for two-dimensional ecological data. Ecology 75, 956–965.

Heilman Jr., G.E., Strittholt, J.R., Slosser, N.C., Dellasala, D.A., 2002. Forest fragmentation of the conterminous United States: assessing forest intactness through road density and spatial characteristics. BioScience 52, 411–422.

Keitt, T.H., 2000. Spectral representation of neutral landscapes. Landscape Ecol. 15, 479–493.

Levins, R., 1966. The strategy of model building in population biology. Am. Sci. 54, 421–431.

Milne, B.T., 1991. Lessons from applying fractal models to landscape patterns. In: Turner, M.G., Gardner, R.H. (Eds.), Quantitative Methods in Landscape Ecology. Springer-Verlag, New York, pp. 199–235.

Milne, B.T., 1992. Spatial aggregation and neutral models in fractal landscapes. Am. Nat. 139, 32–57.

Musick, H.B., Grover, H.D., 1991. Image textural measures as indices of landscape pattern. In: Turner, M.G., Gardner, R.H. (Eds.), Quantitative Methods in Landscape Ecology. Springer-Verlag, New York, pp. 77–103.

O'Neill, R.V., DeAngelis, D.L., Waide, J.B., Allen, T.F.H., 1986. A Hierarchical Concept of Ecosystems. Princeton University Press, Princeton, New Jersey, 254 pp.

Plotnick, R.E., Gardner, R.H., O'Neill, R.V., 1993. Lacunarity indices as measures of landscape texture. Landscape Ecol. 8, 201–211.

Riitters, K.H., O'Neill, R.V, Jones, K.B., 1997. Assessing habitat suitability at multiple scales: a landscape-level approach. Biol. Conserv. 81, 191–202.

Riitters, K.H., Wickham, J.D., O'Neill, R.V., Jones, K.B., Smith, E.R., 2000. Global-scale patterns of forest fragmentation. Conserv. Ecol. 4 (2), 3 http://www.consecol.org/vol4/iss2/art3 (online).

Riitters, K.H., Wickham, J.D., O'Neill, R.V., Jones, K.B., Smith, E.R., Coulston, J.W., Wade, T.G., Smith, J.H., 2002. Fragmentation of continental United States forests. Ecosystems 5, 815–822.

Riitters, K.H., Coulston, J.W., Wickham, J.D., 2003. Localizing national fragmentation statistics with forest type maps. J. Forest. 101, 18–22.

Riitters, K.H., Wickham, J.D., Coulston, J.W., 2004. A preliminary assessment of Montréal process indicators of forest fragmentation for the United States. Environ. Monit. Assess. 91, 257–276.

Vogelmann, J.E., Howard, S.M., Yang, L., Larson, C.R., Wylie, B.K., Van Driel, N., 2001. Completion of the 990s national land cover data set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. Photogramm. Eng. Rem. Sens. 67, 650–662.

Wade, T.G., Riitters, K.H., Wickham, J.W., Jones, K.B., 2003. Distribution and causes of global forest fragmentation. Conserv. Ecol. 7 (2), 7 http://www.consecol.org/vol7/iss2/art7 (online).

Wiens, J.A., 1989. Spatial scaling in ecology. Funct. Ecol. 3, 385–397.

With, K.A., Gardner, R.H., Turner, M.G., 1997. Landscape connectivity and population distributions in heterogeneous environments. Oikos 78, 151–169.

Wu, J., Hobbs, R., 2002. Key issues and research priorities in landscape ecology: an idiosyncratic synthesis. Landscape Ecol. 17, 355–365.