# Use of a Simple Photointerpretation Method with Free, Online Imagery to Assess Landscape Fragmentation

Andrew Lister
USDA Forest Service, Forest Inventory and Analysis/National
Inventory and Monitoring Applications Center
Newtown Square, PA
alister@fs.fed.us

Tonya Lister
USDA Forest Service Forest Inventory and Analysis
Newtown Square, PA
tlister01@fs.fed.us

James A. Doyle
Pennsylvania State University
State College, PA
jamesalexanderdoyle@gmail.com

ABSTRACT: Forest fragmentation is a problem in many areas of the United States. As contiguous forest is divided into smaller and smaller patches, ecosystem services, such as support for water infiltration, microclimate stabilization, wildlife habitat, and human recreation activities become more limited. Researchers and land managers are interested in monitoring forest fragmentation. In this paper we describe an efficient photointerpretation method that automates the work of gathering and loading images. A grid of photo plots is optimally created and overlain on the sample area, and land-use composition is determined using publicly available and web-accessible National Aerial Imagery Program (NAIP) imagery. We present the method in the context of a forest fragmentation assessment for Prince George's County, Maryland, using 2007 NAIP imagery. Methods are described, and include the presentation of a novel, plot-based fragmentation metric. Results indicate that the scale of forest fragmentation in this area, by our measure, is less than 1000 meters, and that our tool can be used efficiently for studies like this.

Keywords: Landscape change; photointerpretation; forest fragmentation

## Introduction

The USDA Forest Service's Northern Forest Inventory and Analysis (FIA) Program collects data related to quantity, quality, distribution, and health of forests from a network of ground plots distributed uniformly across 24 north central and northeastern states. These data are summarized and used to produce annual reports of the trends in and status of the region's forest resources (e.g., McWilliams et al. 2002). To provide contextual information for the analysis of the forestry data, additional data sources are often integrated – e.g., U.S. Census Bureau population data, U.S. Geologic Survey (USGS) land-cover data, and other ancillary GIS information. Combining these data with the forest inventory data allows for multivariate analyses and cross-tabulations that can add depth to analyses. For example, integrating information on forest fragmentation with forest inventory data allows analysts to compare two counties with similar forest-area percentages but different landscape configurations. Interpreting inventory data as it relates to land-cover distribution and composition helps us better understand the status of the forest resource.

Forests in eastern Maryland offer habitat for forest-dwelling species, protect drinking water, serve as buffers for estuarine species against sedimentation and nutrient enrichment, and provide economic and other benefits for humans (Sprague et al. 2006). They are, however, under increasing pressure as the demand for residential development increases (Claggett et al. 2004). Maryland state resource agencies are thus interested in assessing and monitoring land-cover composition and forest fragmentation throughout the state.

Many studies in the past have used remote sensing data to assess landscape fragmentation. For example, Riitters et al. (2002) and Heilman et al. (2002) used classified Landsat satellite imagery from the National Land Cover Database (Homer et al. 2007) to conduct national assessments of forest fragmentation. However, Irwin et al. (2007) found discrepancies between satellite imagery-based data and a digitized GIS dataset of land use derived from aerial imagery, in terms of both patterns and amount of developed land. These discrepancies are generally due to the fundamental difference between what a human interpreter can identify either on the ground or with photography (land use) and what an automatic, statistically based classification of satellite imagery can reveal (land cover) (Irwin et al. 2007).

The goal of this paper is to demonstrate the use of a flexible, inexpensive procedure with which to characterize forest fragmentation using aerial imagery. In addition, we wanted to show how to characterize forest fragmentation using a novel landscape metric calculated from plot-based data. We present this procedure using a case study involving a land-cover assessment of Prince George's county, Maryland. This study is part of a larger, state-level study of change detection in which we use similar techniques.

## Methods

The sampling design we chose for the fragmentation assessment was determined as part of a larger study of land-cover change in Maryland (Lister et al. 2008). We chose 3465 plots in a spatially stratified manner in Prince George's county, Maryland (figure 1), using the sample selection procedure described in Lister and Scott (2009). This procedure uses a fractal (a space filling curve) that covers the entire study area to create a tessellation that partitions the sampling frame into units from which samples are drawn.

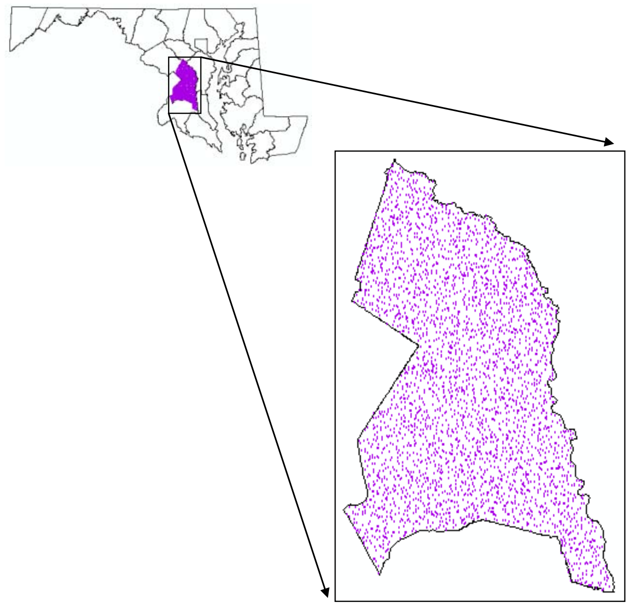


Figure 1. 3465 uniformly distributed, randomly selected plots in Prince George's county, Maryland.

The plot design we chose satisfied two criteria: 1) There were enough subplots to allow for the calculation of a fragmentation metric using a uniform number of paired points in each of the fine-scale separation distance classes (50-m classes between 0 and 250 m); and 2) There was a reasonable number of subplots for a photointerpreter to interpret all plots within the confines of our budget. From past experience (Lister et al. 2008) we determined that 10 subplots per plot would conservatively allow us to finish all 3465 plots within the time allotted for the study. To determine the optimal subplot configuration that would meet our first criterion, we implemented a procedure in which a random set of 10 points was drawn, with replacement, 50,000 times from a set of 25 equally spaced points distributed on a square, 100-m x 100-m grid. For each set of points drawn, we calculated separation distance between each point and every other point in the 10 point sample. Next, we counted the number of pairs of points in each separation distance class and stored the result. We then randomly chose the final plot design we used from among the handful of configurations yielding a uniform count of points per distance class (figure 2). Each separation distance class of the optimal configuration contained nine pairs of points per plot.

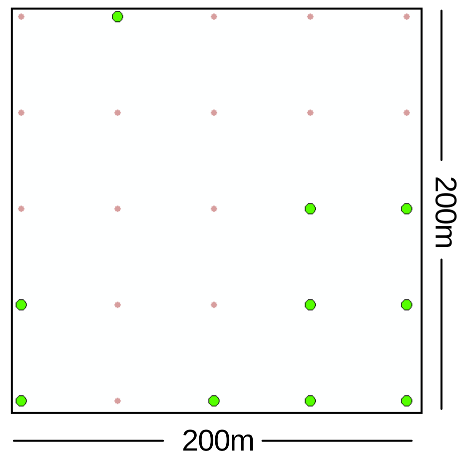



Figure 2. The plot design, consisting of a set of 10 supblots (larger, in green), distributed optimally to achieve an equal number of pairs of points per 50-m separation distance class. Smaller, tan points are part of the set of 25 points from which the optimal configuration was selected via a randomization procedure.

For the fragmentation portion of the study, land-use category was assessed by interpreting digital aerial imagery. The 2007 Maryland imagery consisted of color infrared, leaf-on, 1-m-pixel resolution, digital images from NAIP and served over the Internet using a web-mapping service (WMS). The forest and nonforest land-use categories used were based on an aggregation of more detailed FIA definitions (U.S. Forest Service 2005). A single interpreter was trained and conducted all photo analysis for this study. Quality assurance protocols included a second assessment of a portion of the points by another interpreter, and having the first interpreter re-interpret several hundred points to assess consistency. In both cases, approximately 95% of the interpreter's work met quality standards.

To increase photointerpretation efficiency, an automation method was developed whereby an ArcGIS tool was used to subset imagery from the WMS to areas encompassing and slightly beyond the extent of the footprint of each plot. In other words, "snapshots" of imagery at a scale of 1:4000 were generated, with each image centered on the plot and containing sufficient detail for the interpreter to assess land-use status. The set of 3465 images was stored locally, and displayed using a Microsoft Access form that we developed (figure 3). The form was designed to display the images and allow for data entry in such a way that the number of mouse clicks, wait time for image loading, and data entry were minimized. In addition, links to both "Google Maps" and "Bing Maps" were enabled for each point so that contextual information, and, where possible, Google's "Street View", could be used to guide the interpreter.

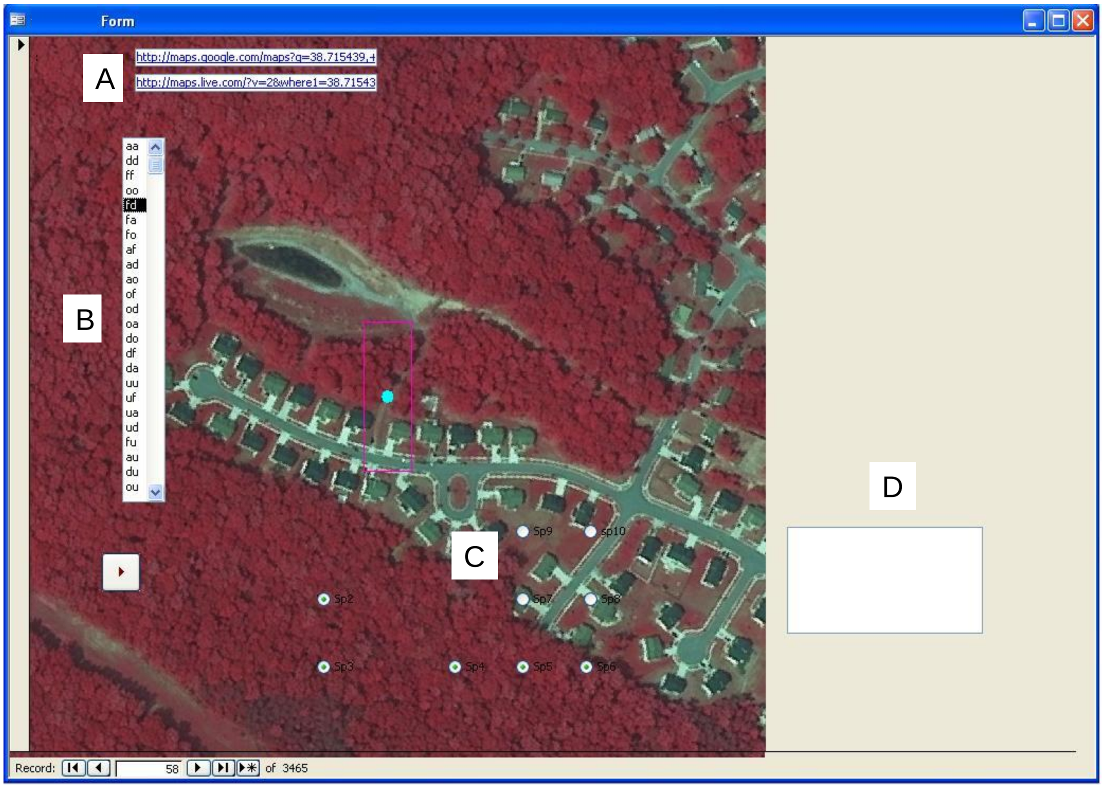



Figure 3. The Microsoft Access form used to record forest fragmentation data. A: the Google and Bing Maps links, which invoke a web browser with a map zoomed to the location of the plot center; B: the set of detailed landuse codes used in the landuse change portion of the study (not presented here); C: the array of 10 subplots assessed for each of 3465 plots – forested subplots are selected and the resulting value is stored in a table; D: an area to enter comments.

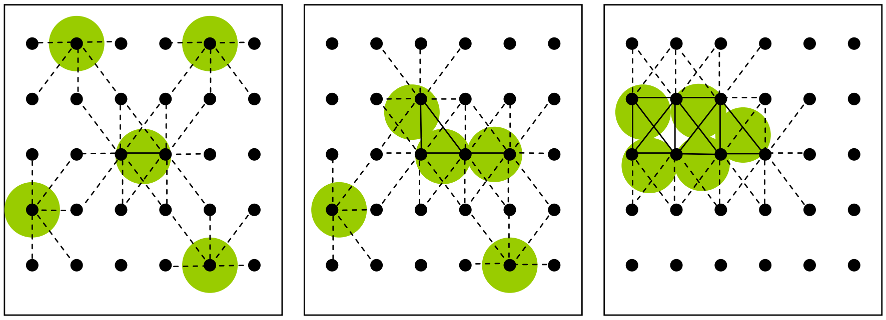
The forest fragmentation metric we chose to calculate, what we call Point Aggregation Index (PAI), is based on the Cluster/Interspersion (CL) index (Miller et al. 1997) and the similar Aggregation Index (AI) (He et al. 2000). The formulation of He et al. (2000) is as follows:

$$AI_i = \frac{e_{i,i}}{\max\_e_{i,i}}$$

where $e_{i,i}$ = the number of pixels of class $i$ that are adjacent to other pixels of class $i$, and max_ $e_{i,i}$ = the maximum possible $e_{i,i}$, or that which would be achieved if all pixels of class $i$ were clumped together with maximum adjacency (for example, a single square clump). We altered this formulation to be as follows:

$$PAI_i = \frac{a_{i,i}}{a_{i,J}}$$

where $a_{i,i}$ = the number of adjacencies between (sub)plots of class $i$ with other (sub)plots of class $i$, and $a_{i,J}$ = the total number of adjacencies between subplots of class $i$ and those of all members of the set $J$ of land-cover classes (which includes class $i$) found in the landscape. Figure 4 gives three examples of how different landscape configurations yield different values of PAI.



$a_{i,i}$ = 1
$a_{i,j}$ = 35
PAI = 1/35, or 0.03

4 $a_{i,i}$ = 4
$a_{i,j}$ = 38
PAI = 4/38, or 0.11

$a_{i,i}$ = 13
$a_{i,j}$ = 37
PAI = 13/37, or 0.35

Figure 4. Three examples of the calculation of PAI. The black dots are sample plots, the green circles represent patches of class *i,* e.g., forest, and the white background represents the other landscape classes. Solid lines represent adjacencies between class *i* and itself, and dashed lines show the same for class *i* and the other landscape class. Adjacency in this example is defined as plots being immediately adjacent in any direction. Holding the area of class *i* constant, as the class's distribution becomes clumpier, PAI increases. Note that class *i* is included as a member of the set *J* of landscape classes.

PAI, like AI, ranges from 0 to 1, and, like AI, it is a class-specific metric of landscape aggregation. It has a maximum value where all (sub)plots of class *i* are only adjacent to members of the same class ($a_{i,i} = a_{i,J}$), -- i.e., the entire landscape is class *i*. It has its smallest value where the class is so disaggregated that there are no two adjacent plots labeled with the class of interest. Finally, its calculation is flexible in that "adjacency" can be defined across multiple scales – i.e., it can be defined within different separation distance classes, in much the same way semivariance is calculated across a range of separation distance classes to create a variogram (Curran 1988).

We calculated PAI for each of the 50-m distance classes at the fine scale (50-250 meters) using all of the subplots in the study, and for the sake of efficiency, calculated it using just one of the subplots per plot at what we term the coarse scale (500-5000 meters), with the following distance class cut-offs: 500, 750, 1000, 2000, 3000, 4000, and 5000 meters. The goal of this effort was to produce a plot of PAI vs. separation distance, and use it to characterize fragmentation at different scales of observation.

## Results and Discussion

The plot of PAI vs. separation distance class is shown in figure 5, and the number of pairs of points per distance class is shown in table 1. As expected, PAI varied at different scales of observation, or in our parlance, for different definitions of adjacency.

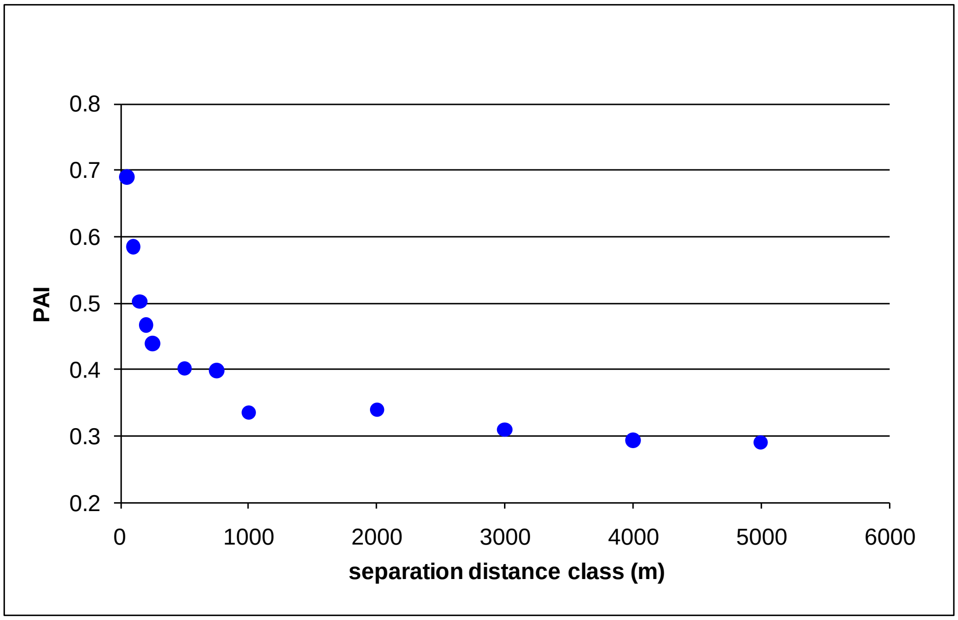


Figure 5. The plot of our fragmentation metric, PAI, vs. separation distance class.

Table 1. The number of pairs of points per distance class (upper threshold, in meters) that went into the calculation of PAI.

| distance class | number of pairs | PAI |
|---|---|---|
| 50 | 31,185 | 0.690 |
| 100 | 31,185 | 0.584 |
| 150 | 31,185 | 0.502 |
| 200 | 31,185 | 0.467 |
| 250 | 31,185 | 0.439 |
| 500 | 4,542 | 0.398 |
| 750 | 8,516 | 0.336 |
| 1000 | 12,176 | 0.339 |
| 2000 | 82,474 | 0.309 |
| 3000 | 130,942 | 0.293 |
| 4000 | 173,802 | 0.290 |
| 5000 | 213,622 | 0.286 |

The pattern of the decay of PAI with distance was expected. The NLCD 2001 map showing the forest/nonforest pattern in Prince George's County, indicates a mosaic of irregularly shaped and sized forest patches (figure 6). This led us to expect a broad range of values, with smaller

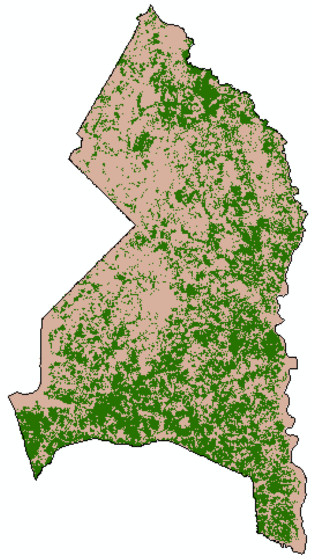


Figure 6. The NLCD 2001 map indicating forest (darker green) and nonforest (lighter tan) patch distribution.

separation distances yielding a higher PAI (the existence of larger, aggregated patches would lead to this), and larger separation distances yielding lower values (separation distances beyond the average patch width, among other things, would cause this). The shape of the relationship indicates that beyond a separation distance of approximately 1000 meters, there is only a small decrease in likelihood that two points chosen at random will both be forest. In other words, the effect of local pattern on the aggregation index diminishes and the effect of landscape-scale pattern begins to take over. We thus conclude that for this landscape, the "scale" of patchiness occurs at less than 1000 meters. Like other metrics, AI and PAI do not by themselves give a full understanding of forest fragmentation – they should be considered one facet of a description of landscape pattern.

We plan to undertake further studies that investigate the significance of this distance – both its physical meaning with respect to patch distribution, shape and size, and its ecological significance. One possible use of this metric is as a tool with which county planners can measure the performance of management practices that promote the aggregation of isolated blocks of forest into more contiguous blocks. The advantage of doing land-cover or use assessments using photointerpretation compared to satellite image classification is that analyses based on aerial photographs are generally more accurate than those done by a computer from satellite images, making results more easily interpreted. In addition, repeat measurements can be made when new photography is available without concern that differences in the satellite sensor or classification algorithm caused false change, as would be the case with the use of AI on a raster image. Finally, metrics like PAI could be calculated on a per-plot basis (as opposed to for the landscape as a whole, like we did in our case study). This would allow for the calculation of sampling errors using classical estimation methods for both overall and change estimates of the metric being used.

We have demonstrated that an efficient photointerpretation procedure can be used to measure forest fragmentation. The automated methods we employed allowed for the interpretation of one plot (10 subplots) every 13 seconds on average. The preparation of our imagery in ArcMap was straightforward and offers the advantage of dramatically curtailing the amount of imagery an analyst needs to load and manage while conducting the analysis. NAIP imagery is free and is generally reflown every 5 to 10 years, making it a good choice for use in monitoring studies; we could assess the same plots in the same way on a new set of imagery when it comes available for Maryland, and report on change in forest fragmentation. Furthermore, the portability of the entire imagery dataset required for this project, which fit on one DVD, was an added benefit.

The Microsoft Access form we created allows for analysts with no GIS software or skills to work as image interpreters. This makes it less costly to hire technical staff because the labor pool that includes those unskilled in GIS is much larger and generally more economical. Finally, our data entry procedure is very efficient and facilitates the integration of Google and Bing maps, making available to the interpreter the imagery and ancillary information that these services provide.

In conclusion, the photointerpretation method we developed is quick, economical, has multiple uses, and due to the convenient tools offered by Microsoft Access and Visual Basic for Applications, can be customized to meet a specific project's needs. Unlike algorithms that generate fragmentation metrics from raster images, our photo-based technique offers the added benefit of a more accurate characterization of landscape composition. We plan to assess the feasibility of implementing this method at regional scales for applications like fragmentation analysis, land-cover change assessments, and natural resource monitoring exercises.

## Literature Cited

CLAGGETT, P.R., JANTZ C.A., GOETZ S.J., and C. BISLAND. 2004. Assessing development pressure in the Chesapeake Bay watershed: an evaluation of two land-use change models. *Environmental Monitoring and Assessment* 94: 129-146.

CURRAN, P.J. 1988. The semivariogram in remote sensing: An introduction. *Remote Sensing of Environment* 24: 493-507.

FORMAN, R.T.T. 1995. *Land mosaics: the ecology of landscapes and regions*. Cambridge, MA: Cambridge University Press. 632 p.

HE, H.S., DEZONIA B., and D.J. MLADENOFF. 2000. An aggregation index (AI) to quantify spatial patterns of landscapes. *Landscape Ecology* 15: 591-601.

HEILMAN, G.E., STRITTHOLT, J.R., SLOSSER, N.C., and D.A. DELLASALA. 2002. Forest fragmentation of the conterminous United States: Assessing forest intactness through road density and spatial characteristics. *Bioscience* 52: 411-422.

HOMER, C., DEWITZ, J., FRY, J., COAN, M., HOSSAIN, N., LARSON, C., HEROLD, N., MCKERROW, A., VANDRIEL, N., and J. WICKHAM. 2007. Completion of the 2001 National Land Cover Database for the conterminous United States. *Photogrammetric Engineering & Remote Sensing* 73(4): 337-342.

IRWIN, E.G., CHO, H.J., and N.E. BOCKSTAEL. 2007. Measuring the amount and pattern of land development in nonurban areas. *Review of Agricultural Economics* 2(3): 494-501.

LISTER, A.J., and C.T. SCOTT. 2009. Use of space-filling curves to select sample locations in natural resource monitoring studies. *Environmental Monitoring and Assessment* 149(1-4): 71-80.

LISTER, T.W., LISTER, A.J., and E. ALEXANDER. 2008. Estimating fine-scale land use change dynamics using an expedient photointerpretation-based method. In: McWilliams, Will; Moisen, Gretchen: Czaplewski, Ray, comps. 2008. 2008 Forest Inventory and Analysis (FIA) Symposium; October 21-23, 2008; Park City, UT. Proc. RMRS-P-56CD. Fort Collins, CO; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 1 CD.

MCWILLIAMS, W.H., ALERICH, C.A., DEVLIN, D.A., LISTER, T.W., STERNER, S.L., and J.A. WESTFALL. 2002. Annual inventory report for Pennsylvania's forests: results from the first two years. Resour. Bull. NE-156. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 71 p.

MILLER, J.N., BROOKS, R.P., and M.J. CROONQUIST. 1997. Effects of landscape patterns on biotic communities. *Landscape Ecology* 12: 137-153.

RIITTERS, K.H., WICKHAM, J.D., VOGELMANN, J.E., and K.B. JONES. 2000. National land cover pattern data. *Ecology* 81: 604.

SPRAGUE, E., BURKE, D., CLAGGETT, S., and A. TODD. eds. 2006. *The state of Chesapeake forests*. Arlington, VA: The Conservation Fund. 115 p.

U.S. DEPARTMENT OF AGRICULTURE, FOREST SERVICE. 2005. Forest inventory and analysis national core field guide, volume 1: field data collection procedures for phase 2 plots, version 3.0. U.S. Department of Agriculture, Forest Service, Washington Office. Internal report. On file with: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis, Rosslyn Plaza, 1620 North Kent Street, Arlington,VA 22209.