Estimating fine-scale land use change dynamics using an expedient photointerpretation-based method

Tonya Lister[1], Andrew Lister[1], and Eunice Alexander[1]

Abstract: *Population growth and urban expansion have resulted in the loss of forest land. With growing concerns about this loss and its implications for global processes and carbon budgets, there is a great need for detailed and reliable land use change data. Currently, the Northern Research Station uses an Annual Inventory design whereby all plots are revisited every 5 years and land use change matrices are estimated using a mapped plot design. These methods have great potential for providing the needed land use change data; however, for many states in the Northern region, these data will not be available until 2013 or later and the ability of these methods to capture finer scale changes, especially those due to urbanization, has not yet been tested. This paper presents an efficient photointerpretation-based change detection 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 change is recorded for two points in time by comparing digital imagery from 1998 and 2007. Results of a pilot test in Maryland show a net loss of forest land with losses due primarily to urban development and most gains in forest land coming from agricultural land uses. Forest losses are largely concentrated around Baltimore and Washington, DC. This pilot study indicates that about 75,000 photo plots would be needed to estimate land use change in Maryland at the county level. This would require approximately 125 hours, about 1.12 minutes per thousand acres, or roughly $1,500. The photointerpretation method presented here could be applied to other states and is well suited for land use change monitoring as the same points could be resampled when new imagery becomes available.*

Keywords: land use change, forest loss, photointerpretation

Introduction

Background

Several recent studies have predicted that urban expansion will continue to be a significant factor affecting forests in many areas of the country. For example, Nowak and Walton (2005) predicted that urban land in the United States would

[1]USDA Forest Service, Northeastern Research Station, 11 Campus Blvd., Suite 200, Newtown Square, PA 19073

In: McWilliams, Will; Moisen, Gretchen; Czaplewski, Ray, comps. 2009. 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.

nearly triple from 2000 to 2050 and that the percent of forest land in urban areas in Maryland would more than double to 37 percent by 2050. Similarly, Stewart et al. (2007) documented the current status of forests on the urban fringe, and highlighted potential impacts that continued urban expansion might have on them. Data from the National Resources Inventory (NRI) reported that more than 10 million acres of forest land were lost to developed land uses between 1982 and 1997 (U.S. Department of Agriculture 2000). Ecological impacts of urban expansion vary, but are generally related to loss of forest or other vegetative cover and increased edge habitat. Loss of forest cover has been shown to lead to loss of soil by both wind (Whiker et al. 2008) and water (Rice and Lewis 1991). It is generally accepted that the loss of topsoil not only lowers the productivity of agriculture and forest ecosystems, but also impacts aquatic ecosystems through sedimentation, nutrient enrichment, and other factors (Faulkner 2004).

The forests of the Chesapeake Bay watershed, many of which are in Maryland, provide benefits to wildlife and human populations. For example, they 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). Maryland state resource agencies are interested in assessing and monitoring land use change in these areas to understand the potential impacts of forest loss on the Chesapeake Bay and to generate needed information for urban planners, wildlife biologists, and other resource managers. Land use change data are also being used in modeling applications, forest resource projections, and carbon budgets (Woodbury et al. 2006).

Land cover products created with satellite imagery have been found to be inappropriate for land use assessments. For example, Irwin et al. (2007) found discrepancies between the satellite imagery-based National Land Cover Database (Homer et al. 2007) and a 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 U.S. Forest Service's Forest Inventory and Analysis Program (FIA) conducts a continuous forest inventory using standardized methods that could be used to assess land cover dynamics. While recent advances in methodology have made it more feasible to monitor land use change using the existing FIA plot design, the data will not become available in Maryland and other states for many years. Furthermore, it is unclear if the sampling intensity of FIA plots is sufficient to meet precision requirements at the county level.

Objectives

To address these challenges, we created a flexible, inexpensive procedure with which to supplement FIA land use change estimates. The objectives of the study were to develop and implement a method with which to conduct a photo-based inventory of land use change in Maryland using FIA definitions. The goal was to not only obtain information useful to federal and state resource agencies, but also to convey information that can help practitioners implement this method in other states or in areas of interest (e.g., watersheds, wildlife areas, ecoregions).

Methods

Sample Design Development

To estimate land use change, we first had to develop a plot design. We decided the plot would consist of at least one subplot made up of a single point at which a photointepretation (PI)-based land use category would be assessed. From past experience, we determined that this type of plot is most amenable to rapid PI using FIA definitions. The NLCD change product (Homer et al. 2007) was used to determine the optimal subplot count and configuration and to assess various subplot arrangements. Although not PI-based, the NLCD data were used because they are the only spatially explicit and consistent land change data source that covers large analysis areas. The NLCD change product is a pixel-based GIS dataset in which each 30-m pixel is assigned a land cover change category based on comparisons of satellite imagery from circa 1990 and circa 2000. Focusing on forest loss, we first recoded the NLCD change product such that each pixel was labeled forest loss (1) or other (0). We then randomly generated 100 plots per county, with each plot consisting of an array of 25 subplots arranged in a square grid with 100-m spacing (Fig. 1). These plots sampled the NLCD change product-derived forest loss data using different numbers of subplots per plot. The sampling errors were determined for 10 randomly selected configurations of subplots for each subplot count category up to 10 subplots. Using these results, we calculated the total cost to achieve an acceptable level of precision (which we arbitrarily defined as generally having a sampling error no more than 20 percent of the county-level estimate) using the following equations:

$$N_{required} = ((t_{\alpha,\, n-1} * cv) / E)^2 \qquad \text{equation 1}$$

and

$$Cost = a(N_{required}) + i*b(N_{required}) \qquad \text{equation 2}$$

where $N_{required}$ = the sample size required to reach the desired precision, $t_{\alpha,\, n-1}$ = the critical value of the t distribution associated with a sample size of *n* at the 1-α confidence interval, cv=the coefficient of variation, E = the desired precision expressed as the desired proportion of the mean that the confidence interval will represent -- in this case, 0.2, i = the number of subplots in the design, a = the cost in time required for the photointerpreter to switch between plots -- in this case, 1 second, and b = the time required to complete a single subplot -- in this case, 6 seconds.

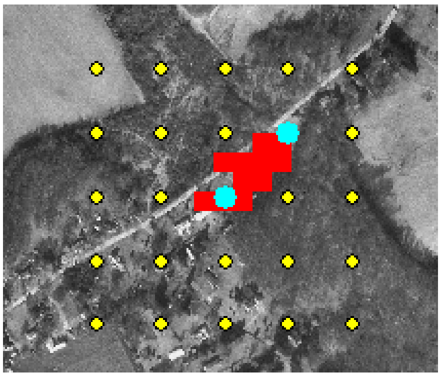

Figure 1. The 25-subplot design used in the first part of the study involving the NLCD change product. The subplots were arranged in a square grid with 100-m spacing. When subplots intersected the NLCD change category labeled forest loss (in red), they were counted, and the proportion of subplots counted in this manner was assigned to the plot for estimation purposes.

PI Methods

After determining which plot design minimized total cost and met precision requirements, we established a spatially balanced plot network consisting of 50,000 randomly selected plots across Maryland using a fractal-based tessellation approach described by Lister and Scott (2009). We divided the plots into 10 panels, each consisting of 5000 plots evenly distributed across the State. This paper discusses the results from one panel (5,000 plots) of data. These data were then used to reevaluate the number of plots needed for county-level estimates of land use change in Maryland, using the same methods as described above, only with the PI data instead of the NLCD change product data.

Land use category was assessed at two points in time (1998 and 2007) on each subplot by interpreting digital aerial imagery. The 1998 imagery consisted of panchromatic, leaf-on, 2-m-pixel resolution, digital orthophoto quadrangles (DOQs) from a state-level imagery dataset stored locally in an ArcGIS raster catalogue. The later date imagery consisted of color infrared, leaf-on, 1-m-pixel resolution, digital imagery from the National Agriculture Imagery Program collected for Maryland in 2007 and served over the Internet using a Web-mapping service (WMS). Land use categories used were based on an aggregation of more detailed FIA definitions (U.S. Forest Service 2005) including Forest, Agriculture, Developed, and Other Nonforest. A single interpreter was trained and conducted all PI for this study.

To increase PI efficiency, an automation method was developed whereby an ArcGIS tool was used to subset imagery from the raster catalogue and 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 change. The two sets (1998 and 2007) of 5,000 images were stored locally, and displayed using a Microsoft Access form that we developed (Fig. 2). 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 to loading, and data entry were minimized.

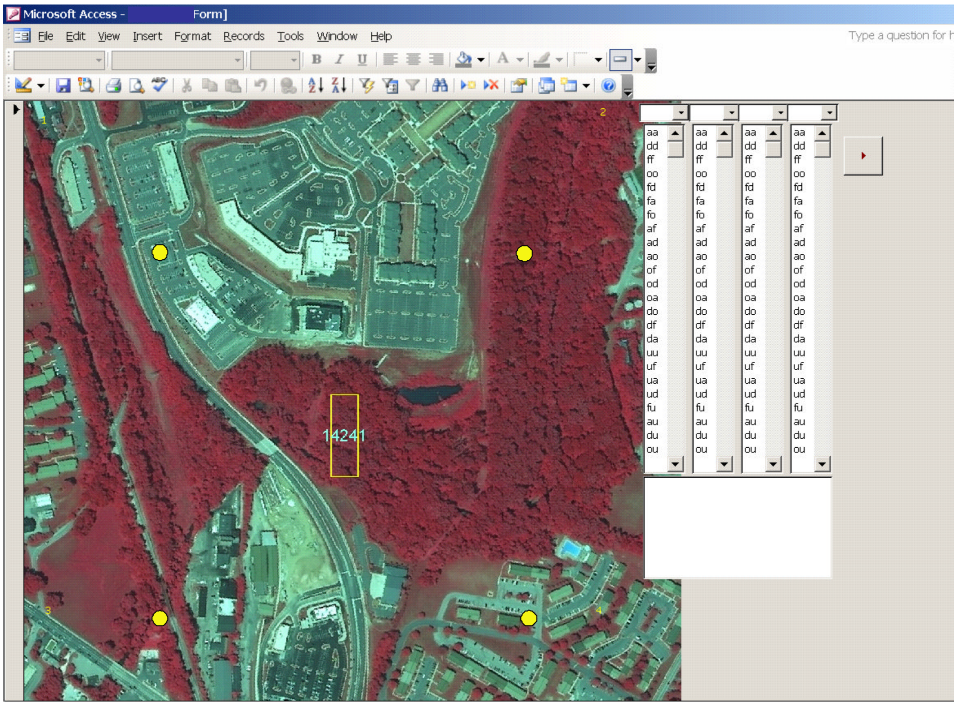

Figure 2. The MS Access form used to enter data and display imagery. Subplots are shown as dots at each corner of photo and rectangle in center is an acre area used as a reference guide. Data entry table for each subplot shown on right with all possible combinations of land use classes displayed.

Data from the 5000 plots were analyzed using the simple random sample estimator (Zar 1999), and estimates of the total areas of land use change categories were calculated, along with associated precision estimates. In addition, equation 1 was used to calculate the number of plots (and subplots) required to achieve acceptable precision, given a more realistic, optimized PI procedure and plot and sample design.

Results and Discussion

Pilot Plot Design Results

Figure 3 presents results of our evaluation of how various combinations of subplot counts and configurations affect sampling error, based on estimates of forest loss from the NLCD change product. As subplot count increased, large improvements in precision were observed until the subplot count reached 5 and then the rate of improvement was less pronounced. In other words, the change in the precision level after 5 subplots was not large enough to warrant the additional cost and time to add additional subplots into the final design. For plots with 3 and 4 subplots, we also graphed the average sampling error for those plots where the distance between subplots was maximized. In the best arrangements, subplots were located at the extremes of the subplot grid, where the intersubplot distances were maximized. One would expect this to be the case – subplots located farther apart are more likely to acquire different information about the landscape, making plot level summaries closer to the sample mean and thus lowering the variance of the overall estimate.

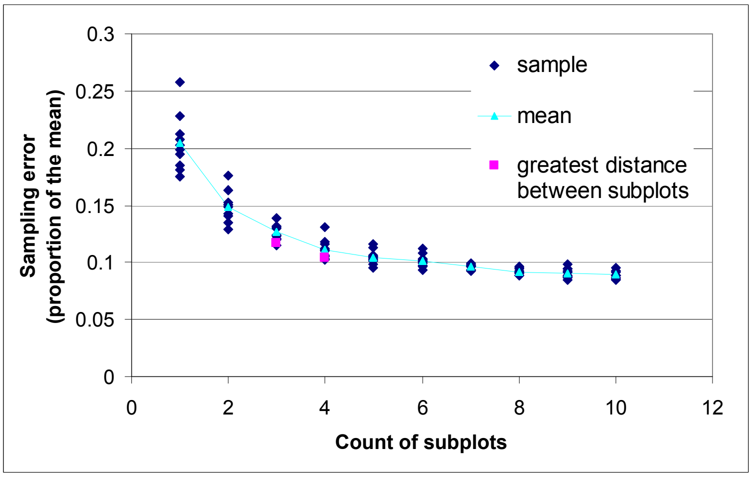

Figure 3. The relationship between subplot count (various configurations) and sampling error of estimates of area of forest loss from a set of plots that were intersected with an image depicting estimates of forest loss from the NLCD change product.

We conducted our cost analysis based on these results, using costs associated with between 1 and 5 subplots. With the cost function we chose, we determined that 3 subplots would be the optimal subplot count (Fig. 4). However, for our PI pilot study, we decided to use a 4-subplot design so as not to limit analysis opportunities. Subplots were arranged in the corners of a square pattern with vertical and horizontal distances of 500 m. This was the greatest practical distance given the constraints of the photo image resolution and size.

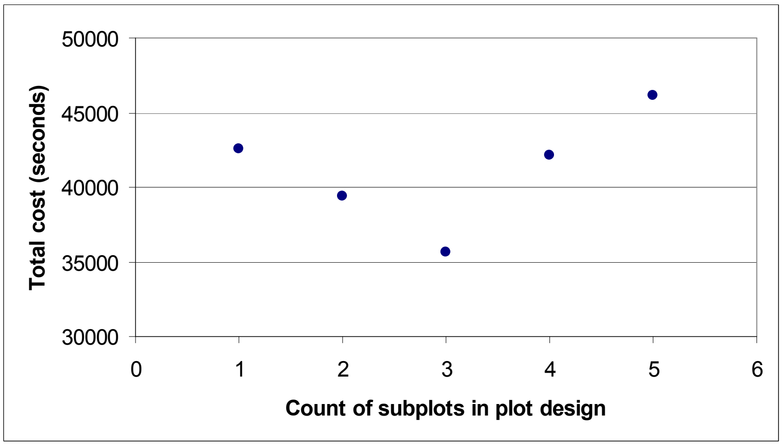

Figure 4. The relationship between cost and count of subplots. The optimal count was the point at which the cost was minimized.

Land Use Change Results

Land use change results from the PI pilot study show a net loss of 28,000 acres of forest land in Maryland from 1998 to 2007, which averages to be more than 3,000 acres per year (Fig. 5). The gross forest loss (66,000 acres) was primarily due to conversion to development, accounting for 91 percent of the total forest loss. Most forest gains were from agriculture (91 percent). The loss of forest land to development is an expected result, as Maryland experienced increases in population and housing densities during this period.

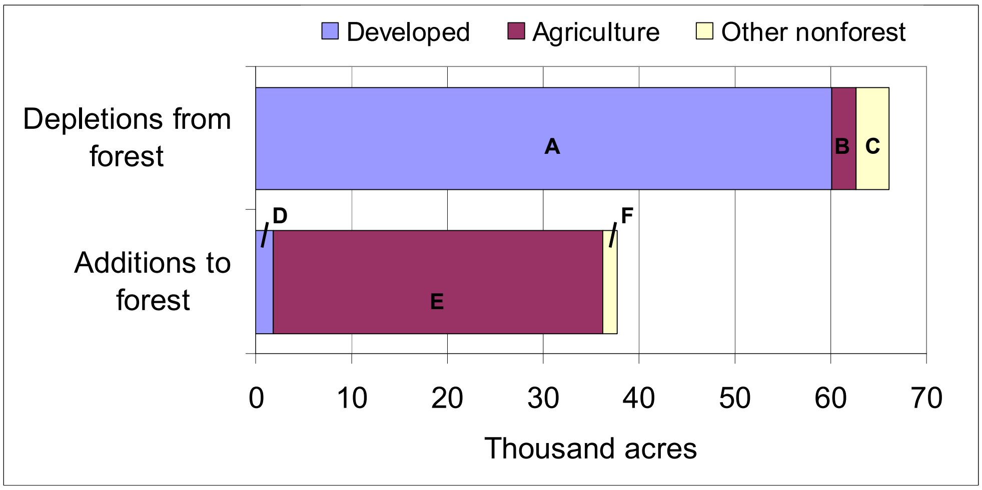

Figure 5. Estimates of areas of different land use change categories. Sampling errors are as follows: A: 7.9%; B: 35.3%; C: 32.1%; D: 33.3%; E: 9.9%; F: 44.7%.

Figure 6 shows the distribution of forest loss in Maryland between 1998 and 2007. There is a high proportion of forest loss plots in the growing suburbs of Baltimore and Washington D.C., an area of the state that has experienced the greatest pressure from urban expansion. For example, the highest proportion of forest loss plots is found in Prince George's county, which borders Washington D.C. From 2000 through 2007 more than 22,000 new housing units were approved for construction, making this one of the fastest growing counties in the state (Maryland Department of Planning 2007).

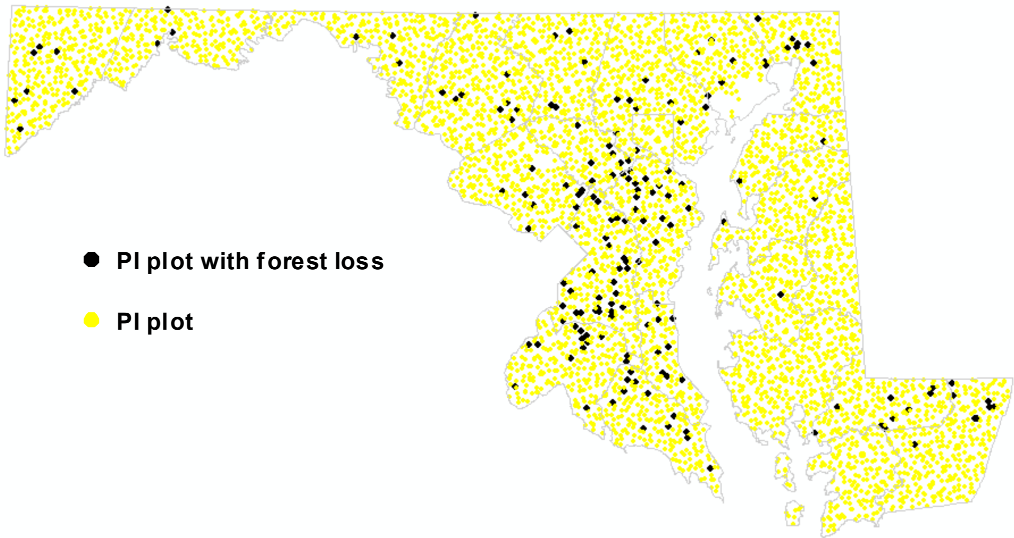

Figure 6. Distribution of land use plots highlighting plots showing forest loss, 1998-2007, Maryland.

Reevaluation of Study Design Using Pilot Results

During this study, we made improvements in image viewing and data entry methods that substantially lowered the cost (in terms of time) involved in switching between photos. With these new techniques, the cost of switching between plots in terms of file opening and image loading time was reduced. As our initial estimate of one second of time spent switching between photos neared zero, the time associated with doing a single plot of 4 subplots was not substantially different from doing 4 single-subplot plots. We therefore determined that the optimal sampling protocol for future work would be a single subplot plot.

Using results from the pilot study, we reevaluated the number of plots that would be necessary to estimate land use change at the county level in Maryland with acceptable precision (having a sampling error no more than 20 percent of the county-level estimate). Each county has a separate requirement for the number of plots needed, and there are some important things to consider when determining what plot density is best. If the end user's goals are monitoring and regional analyses, then a uniform density of plots across the state would be preferred. The plot density needed for each county ranged from one plot per 28 to 333 acres. The counties where we would expect the greatest amount of forest land change as suggested by U.S. Census and Maryland planning data would be sufficiently sampled with a plot density of one plot per 91 acres, so we decided to use this as our plot density requirement across the state. Therefore, we estimated that 75,000 plots would be needed in Maryland for county-level estimates of land use change. Results from the study show that, on average, 10 points can be photointerpreted per minute. To complete the PI work for the whole state, this translates to approximately 125 hours—just over 3 weeks of full-time work, or approximately $1,500.

This method could be applied to other states, and cost could be easily estimated for a certain level of precision. Because images generated for the PI work are snapshots, there is no wait-time for new images to load and there is no need for network connections. More than 5,000 images can easily fit on a single DVD, making the procedure mobile and efficient. The method is also well suited for monitoring. When new imagery is flown, the same PI points can be measured allowing for time series analyses of land use change.

References

Faulkner, S. 2004. Urbanization impacts on the structure and function of forested wetlands. Urban Ecosystems. 7(2): 89-106.

Homer, C.; Dewitz, J.; Fry, J.; Coan, M.; Hossain, N.; Larson, C.; Herold, N.; McKerrow, A.; VanDriel, N.; Wickham, J. 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.; Bockstael, N.E. 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.

Maryland Department of Planning. 2007. New housing units authorized for construction (2000-2007). Available online at: <http://www.mdp.state.md.us/msdc/NEWHH/2007/annual/Table2A_2007.xls>. [November 25, 2008].

Nowak, D.J.; Walton, J. 2005. Projected urban growth (2000–2050) and its estimated impact on the US forest resource. Journal of Forestry. 103(8): 383-389.

Rice, R.M.; Lewis, J. 1991. Estimating erosion risks associated with logging and forest roads in northwestern California. Water Resources Bulletin. 27(5): 809-818.

Sprague, E.; Burke, D.; Claggett, S.; Todd, A., eds. 2006. The state of Chesapeake forests. Arlington, VA: The Conservation Fund. 115 p.

Stewart, S.I.; Radeloff, V.C.; Hammer, R.B.; Hawbaker, T.J. 2007. Defining the wildland urban interface. Journal of Forestry. 105:201-207.

U.S. Department of Agriculture. 2000. Summary Report: 1997 National Resources Inventory (revised December 2000). Natural Resources Conservation Service, Washington, DC, and Statistical Laboratory, Iowa State University, Ames, IA. 89 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.

Whicker, J.J.; Pinder J.E.; Breshears, D.D. 2008. Thinning semiarid forests amplifies wind erosion comparably to wildfire. Journal of Arid Environments. 72(4): 494-508.

Woodbury, P.B.; Heath, L.S.; Smith, J.E. 2006. Land use change effects on forest carbon cycling throughout the southern United States. Journal of Environmental Quality. 35:1348-1363.

Zar, J.H. 1999. Biostatistical analysis. Upper Saddle River, NJ: Prentice Hall. 663 p.