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# Proceedings of the Sixth Annual Forest Inventory and Analysis Symposium

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Documents contributions to forest inventory in the areas of sampling, remote sensing, modeling, information management and analysis for the Forest Inventory and Analysis program of the USDA Forest Service.

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## Preface

The Sixth Annual Forest Inventory and Analysis Symposium was held September 21–24, 2004, in Denver, CO. The symposium was integrated with the Monitoring Science and Technology Symposium sponsored in part by the U.S. Department of Agriculture Forest Service Rocky Mountain Research Station. As with recent symposia in the series, we continue to experience a broadening of the range of presentation topics and welcome contributors from outside the formal Forest Inventory and

Analysis program. The symposium organizers thank all participants and presenters and convey special thanks to those who submitted their papers for these proceedings.

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Gregory A. Reams  
Paul C. Van Deusen  
William H. McWilliams



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## Vision for the Future of FIA: Paeon to Progress, Possibilities, and Partners

Richard W. Guldin,<sup>1</sup> Susan L. King, and Charles T. Scott<sup>2</sup>

**Abstract.** — The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture Forest Service has made significant progress implementing the annualized inventory in 46 States in 2004. Major increases in program performance included the availability of plot data and the plots' corresponding approximate coordinates. A mill site study and biomass models were used to compare actual versus approximate coordinates. The protocols used to protect the privacy of private forest landowners did not meaningfully alter the results. A new strategic plan for FIA will be developed for 2007–12. Through meetings with partners and customers, FIA will evaluate opportunities to broaden the information collected and analyses of this data.

### Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service has nearly completed the transition to an annualized inventory approach that incorporates forest health detection monitoring and uses state-of-the-art geospatial technologies. Web delivery of results is increasing. The principles of continuous improvement are being applied to the FIA program, focusing on those aspects identified by users as most important. The program is poised to begin a second round of strategic planning for 2007–12. Partners will play key roles in the strategic planning process to evaluate and prioritize the future possibilities and help the program achieve its goals.

### Progress

In fiscal year (FY) 2003, the annualized FIA program had field operations in 46 States. Measurements were taken across the landscape, covering 71 percent of the forest land in the United States,<sup>3</sup> an increase of 9 percent over the area covered in FY 2002. A total of 43,034 Phase 2 (P2) plots, the traditional ground sample, and 3,740 Phase 3 (P3) plots were remeasured. P3 plots measure additional variables that indicate forest health.

Users' needs were met in a variety of ways. FIA program analysts engaged in 1,450 significant consultations with users, an increase of 41 percent from the previous year. Users made nearly 15,000 downloads of data from the FIA Web site, a 20-percent increase over the previous year. Web tracking software identified the data most frequently downloaded, and this information was used to focus continuous improvement activities.

During the past 2 years, technical specialists have revised the FIA Field Guide for Phase 2 Measurements (<http://www.fia.fs.fed.us/library/field-guides-methods-proc/>). A substantial number of changes in field procedures had been proposed to simplify fieldwork and make it more efficient. A major revision of the guide, version 2.0, was released in January 2004. Data recorder and compilation software were upgraded in response to the new field guide so that its protocols could be implemented during the 2004 field season.

### Privacy Policy

The privacy policy adopted a year ago in response to the new legislative language in the FY 2000 Interior Appropriations Bill continues to attract the attention of external users and analysts.<sup>4</sup>

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<sup>3</sup> This percentage includes the acreage of forest land in interior Alaska. In prior years, the percent coverage excluded interior Alaska. With plans now in place to begin work in interior Alaska in FY 2005, reports of area covered in FY 2003 and beyond will include interior Alaska.

<sup>4</sup> Section 348 of H.R. 3423, Department of the Interior and Related Agencies Appropriations Act of 2000. (Nov. 17, 1999). H.R. 3423 was incorporated by cross-reference in the conference report into H.R. 3194 [Division B]. H.R. 3194, the FY 2000 Consolidated Appropriations Bill, became Public Law 106-113 on Nov. 29, 1999.

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The goal of the policy is to protect the privacy of private forest landowners who allow FIA field crews to collect data on their property. The policy ensures that data for any plot cannot be linked *with certainty* to the participating private landowner.

Two-thirds of the forest land in the United States is privately owned. Permission to collect data on private lands is vital to the continued credibility of the FIA program. In recognition of the importance of private landowner participation in the FIA program, FIA was placed under the same privacy protection provisions as other critical agricultural inventory, monitoring, and census programs operated by the National Agricultural Statistical Service (NASS). A new privacy law was not created for FIA. Rather, Congress gave private forest landowners participating in the FIA program the same legal protections already enjoyed by farmers participating in the other USDA programs.

The pre-1998 FIA privacy policy was updated to comply with the law. NASS and the USDA Office of the General Counsel (OGC) were consulted to ensure that the legislative intent was faithfully implemented in the new policy. USDA's long experience with the same legislative language in other USDA programs provided a sound foundation for developing the new FIA policy.

Based on experience with the other USDA agricultural crop inventory programs operated by NASS, OGC did not believe that "fuzzing" (providing an approximate location) alone was sufficient to meet the terms of the legislation. FIA national program staff and members of the FIA Statistics Band consulted with experts from the American Statistical Association and the U.S. Census Bureau to learn what techniques they advocated for ensuring the privacy of individuals participating in surveys. The experts believed that a small amount of "swapping" (switching the locations of two similar plots) would be much more effective than coarse "fuzzing." Indeed, with a small amount of "swapping," the statistical experts believed that "fuzzing" could be radically reduced, and the combination of "swapping" with reduced "fuzzing" would improve the quality and usefulness of the publicly available data while providing the minimal amount of privacy protection required. OGC concurred.

To understand what impact the new policy might have on analyses performed with data from FIA's public database, the two techniques must first be understood. "Fuzzing" consists of randomly adjusting the latitude and longitude locations of the plot. Under the old, pre-1998 FIA privacy policy, a combination of latitude and longitude were rounded to the nearest 100 seconds. This meant that users could be certain that the actual plot location fell within the 2,010 acres surrounding the plot location contained in the FIA public database. Under the new FIA privacy policy, latitude and longitude are randomly located within one-half mile. This means that the actual plot location is masked within only a 500-acre area. Users commenting on the draft privacy policy applauded the fourfold reduction in fuzz compared to the old policy.

"Swapping" consists of exchanging the plot coordinates for a small number of *similar plots within close proximity and in the same county*. Swapping only occurs on private forested plots and depends on the region of the country. Between 0 and 10 percent of the forested plots are randomly selected for swapping with plots from the remaining data for a total swapping of between 0 and 20 percent. The primary criterion for swapping is based on a measure of ecological similarity. Plots with the smallest ecological difference are swapped. The variables for swapping—e.g., x and y coordinates, forest type group, and stand size—vary by region. This induces enough uncertainty as to the actual property owner to satisfy the legal requirements without introducing an unacceptable amount of error in the population estimates computed for analyses.

What are the impacts of fuzzing and swapping on analyses? In general, any analysis that requires computation of population estimates using entire counties will be completely unaffected. By definition, swapping is limited to plots in the same county. Therefore, when all FIA plots in one or multiple counties are used to compute population estimates, all the data are used. Because population estimates at subcounty scale already have a relatively high mean square error due to the small number of plots, the error contribution of swapping is likely to be small in

comparison to the error due to the small sample size.<sup>5</sup> No other data for the plot are swapped other than the plot coordinates. Therefore, all the other relationships within and among the variables for the plot are retained.

Data that have been fuzzed and swapped are not suitable for geospatial analyses in which FIA data are used to validate pixel classifications derived from satellite imagery. For this type of validation work, actual plot coordinates are required to properly register the ground data with the imagery. To serve such needs, the FIA program has created National FIA Spatial Data Services at the Northeastern Research Station and regional centers at the other four FIA units. The centers will populate data layers or prepare derived products using actual coordinates for FIA clients. Routine requests are fulfilled in several days or up to several weeks. More complex requests take longer. For especially complex and intensive data modeling, mapping, or analyses beyond the scope of Spatial Data Services, two additional options exist. Clients can visit a Spatial Data Services center to work directly with the data under the supervision of FIA staff, or FIA partners (those furthering FIA's mission) can negotiate a confidentiality agreement with the FIA program to use data for a specific purpose and time.

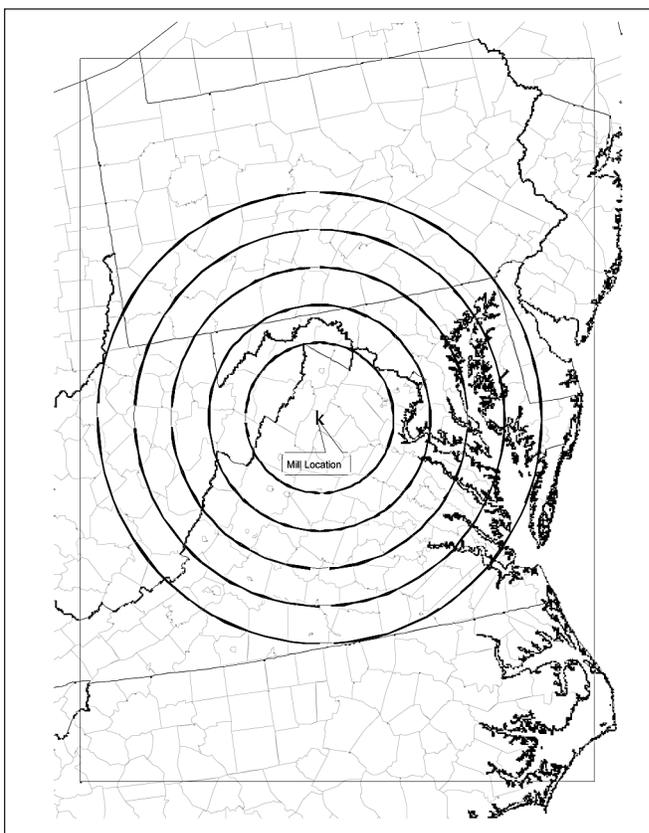
Some questions continue to persist about the use of the data in the FIA public database after fuzzing and swapping according to the new policy. Allegations and assertions have been made that the public database is useless, and that analyses, such as mill studies, cannot be reliably made from the public database. For this article, two special studies were conducted to test the hypothesis that the public database will produce results that are substantially different than if the actual plot locations were used.

### Mill Site Case Study

A common data request to FIA from private industry is to calculate woodshed information within a specified geographic distance

of a proposed mill. A prospective mill site was selected in the Shenandoah Valley of Virginia, (fig. 1). Woodsheds of five different radii—50, 75, 100, 125, and 150 miles—were evaluated to determine the acreages of forest and timberland, the numbers of live trees 1 inch and greater in diameter at breast height (d.b.h.), the number of growing-stock (GS) trees 5 inches and greater in d.b.h., and the cubic foot and board foot volumes (gross and per acre) of timber in the prospective woodsheds. Table 1 shows the results.

Figure 1.—The five concentric circles surrounding the proposed mill location correspond to radii of 50, 75, 100, 125, and 150 miles, respectively. The circles cross State boundaries and different FIA regions, which may have used different variables for swapping. Each circle includes both complete and partial counties.



<sup>5</sup> If a volume estimate is wanted for a 30,000-acre tract, for example, using data from the FIA database is likely to only yield four or five plots within that polygon. Computing population estimates for the tract based on so few plots will probably yield estimates with large mean square errors; if one of those plots happens to be swapped, the impact may be noticeable. Rather than bemoaning the potential impact of having a swapped plot in the population, however, the more important question is why one would be willing to impute total volume on the tract on the basis of such a limited sample of plots in the first place. Polygons for analysis should be large enough to yield 30 to 40 forested plots—200,000 to 250,000 forested acres—before population estimates and mean square errors are used to impute population totals.

Table 1.—Comparison of actual versus fuzzed and swapped summaries for several radii (50, 75, 100, and 150 miles).

Retrieval type	Area (1,000s of acres)			Trees (1,000s)		Volume (millions)		Volume/acre	
	Total	Forest	Timber-land	Live (≥ 1")	GS <sup>a</sup> (≥ 5")	ft <sup>3</sup>	Bd. Ft.	ft <sup>3</sup>	Bd. Ft.
<i>50-mi radius</i>									
Actual	5,027	2,763	2,532	1,273,234	301,828	4,315	14,594	1,704	5,764
Fuzz/swap		2,777	2,542	1,277,453	301,729	4,322	14,632	1,700	5,756
<i>75-mi radius</i>									
Actual	11,310	6,659	6,181	3,459,449	807,015	11,163	36,155	1,806	5,849
Fuzz/swap		6,639	6,161	3,424,786	802,263	11,085	35,907	1,799	5,828
<i>100-mi radius</i>									
Actual	20,106	11,848	11,224	6,576,872	1,502,825	20,477	65,605	1,824	5,845
Fuzz/swap		11,850	11,223	6,570,391	1,501,532	20,496	65,773	1,826	5,861
<i>125-mi radius</i>									
Actual	31,416	18,228	17,487	10,569,005	2,355,062	32,069	102,361	1,834	5,854
Fuzz/swap		18,223	17,487	10,536,468	2,350,409	32,011	102,194	1,831	5,844
<i>150-mi radius</i>									
Actual	45,239	25,538	24,682	15,158,820	3,359,473	44,773	141,290	1,814	5,724
Fuzz/swap		25,568	24,722	15,176,113	3,361,850	44,780	141,288	1,811	5,715

<sup>a</sup> GS = growing stock.

The results show that the differences between using actual versus fuzzed and swapped plot locations are trivial for this mill site study. The differences are due to fuzzed and swapped plots in partial counties within the radii. Because the results are consistent across potential woodsheds of five different radii and for all the major variables that are normally a part of a mill site feasibility study, the trivial nature of the differences between the two sets of data do not appear to be an aberration.

### Biomass Map Case Study

A spatial analysis was conducted to test the usefulness of the fuzzed and swapped data for producing models of mapped attributes. Using satellite imagery to model and map attributes of forests has become very popular. The spatial resolution of orbiting sensors varies significantly from less than 10 m (IKONOS, QuickBird) to 1,000 m (Advanced Very High Resolution Radiometer [AVHRR]). Several mid-resolution sensors, such as Landsat (30 m) and Moderate Resolution Imaging Spectroradiometer (MODIS) (250–500 m), offer especially useful resolution for studying forest attributes over wide areas. The twin challenges to using digital data from satellite sensors are (1) developing models to classify the images by

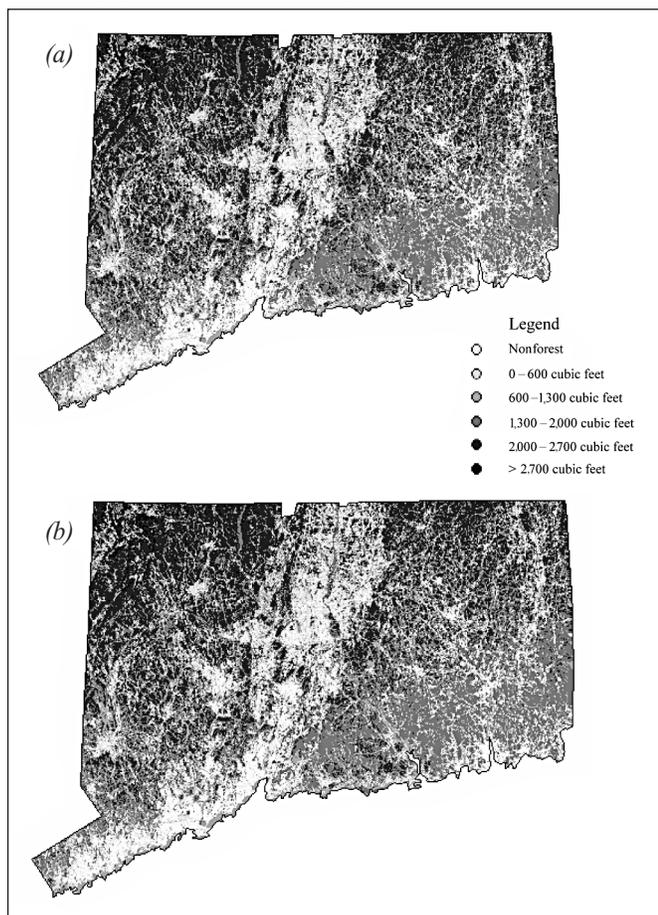
individual pixels or groups of pixels, and (2) using ground-based data to validate the classification models. The former challenge is relatively easy. The latter challenge is more difficult. FIA plot data are among the best ground-based sets of data that can be used to validate classification models. For example, the interagency team developing the Multi-Resource Land Cover classification models relies on FIA plot data for validation of forest cover type models. FIA data also were key to developing the forest cover type map contained in the National Atlas ([www.nationalatlas.gov/mld/foresti.html](http://www.nationalatlas.gov/mld/foresti.html)) and is based on a 1991 map using AVHRR imagery.

The hypothesis tested by this case study is that the publicly available plot data in the FIA database will yield model validation results no different from actual plot data. This hypothesis was tested by building a forest biomass map for Connecticut. The map was created by modeling above-ground forest biomass using road densities, satellite data, and the x and y coordinates of FIA plot data. The road density from the plot center within varying pixel radii was computed using 1:100,000 Tiger/Line road data from the U.S. Census Bureau. Two independent variables derived from satellite imagery were included in the

model. The first satellite variable was created from a reclassified forest/nonforest map acquired from a National Land Cover Data set. The second satellite variable was calculated from six of the seven Landsat Thematic Mapper bands using the tasseled cap transformation for greenness.

The  $R^2$  for both the actual and the publicly available coordinates was 0.43. The intercepts accounted for the largest difference in the coefficients of the two models. The standard errors of the coefficients for two models were equivalent. Figures 2a and 2b reveal the similarity of the maps resulting from the model with exact coordinates and the model with the publicly available coordinates.

Figure 2.—Biomass maps for Connecticut using (a) actual plot coordinates and (b) publicly available plot coordinates. Although the two maps appear identical, the predicted values do not always fall in the same cubic-foot volume class.



### What Can Be Inferred From the Two Case Studies?

In developing the approach to satisfy privacy concerns, FIA statisticians consulted with counterparts in several other agencies and organizations that are responsible for programs that rely on sampling. During those consultations, two points were consistently made by the other agencies and organizations: (1) swapping did not induce significant deterioration in the quality of their program's data to the detriment of their clients; and (2) nothing indicated that nontrivial differences would emerge from the algorithms adopted by FIA. The peer review that was conducted before issuing the new privacy also uncovered no problems with the approach proposed by FIA. These results bear out the wisdom of the advice FIA received and the quality of the internal testing performed before issuing the new privacy policy.

The results of the mill site case study dispel recent allegations that the approach taken by FIA to protect the privacy of partners seriously damaged the usefulness of the publicly available FIA data. The database can be used with confidence for projects such as mill site studies and woodshed analyses.

The results of the biomass map case study suggest that using the new publicly available data does not compromise the ability to model attributes, at least when using imagery of 30 m or larger resolution. The fourfold reduction in fuzz in the new public database appears to have improved the utility of the data for geospatial analyses. The "noise" in the model data set due to Global Positioning System errors and the georeferencing of Landsat pixels is probably similar to the noise induced by the fuzzing and swapping algorithms.

The FIA program is willing to conduct additional case studies, both in other regions and for different types of studies, to demonstrate the utility of the publicly available FIA data. Perhaps different results will be obtained for mill site studies in regions that are substantially different from the conditions existing in this study area (e.g., 50- to 60-percent forest cover; 90 to 95 percent of forest land being timberland; growing stock between 20 and 25 percent of total stocking; and per acre volumes of 5,500 to 6,000 board feet).<sup>6</sup> One reason this case study region was selected is that its conditions are very similar to

<sup>6</sup> Individuals wanting to partner with the FIA program in conducting additional tests of the publicly available FIA data for projects such as mill site studies should contact the author directly. The only caveat the author requests is that the results of the tests be published in a future FIA Science Symposium or equivalent outlet.

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many other areas across the United States. Consequently, the results reported herein are believed to be broadly applicable. An unusual suite of conditions may lead to different results, however, and the FIA program is interested in exploring the utility of the publicly available data set in such conditions.

The biomass map case study sheds little light on the usefulness of the public FIA database for modeling with imagery of higher resolution (10 m or less). We believe, however, that locational errors likely will be of similar magnitude. It may be that actual plot coordinates are needed to work with high-resolution images over large areas, assuming that very accurate rectification of images occurs. The FIA program is very interested in conducting tests with partners using high-resolution imagery.

As more experience is gained with the publicly available database, which kinds of analyses and which spatial scales may require the use of actual coordinates will become clearer. National FIA Spatial Data Services at the Northeastern Research Station is available to assist with special needs. Over the past year, the center has consistently enabled clients to meet their deadlines, even when clients had only 3 or 4 months to complete their analytical work. Clients with short deadlines are encouraged to make those known in their initial contact with Spatial Data Services at [www.fs.fed.us/ne/fia/spatial/index.html](http://www.fs.fed.us/ne/fia/spatial/index.html).

## **FIA Program Plans**

### **Looking Ahead to 2005 and 2006**

The FIA program has adopted two slogans for FY 2005 and FY 2006: “Lose No Ground” and “No State Left Behind.” As additional States have been added to the annualized inventory program, FIA Program Managers have focused on postponing annualized inventory work if reasonable assurances do not exist that the annualized work can be continued in subsequent years—“Lose No Ground.” Adding new States has been neither simple nor easy. Hiring, training, and retaining field crew members have been difficult at some stations and in some States. Consequently, full panels of data collection have not always been collected in a single field season. Further, during bad fire seasons when some State and Federal crew members are pulled away from FIA

duties to fight wildfires, all the fieldwork anticipated has not been performed. When some fieldwork has been carried over to the next field season, known as “panel creep,” Program Managers working with State forestry agency partners have worked hard to gain efficiencies and eliminate the fieldwork backlog. Recent experience shows that panel creep can be reduced and eliminated. Completing a full panel of fieldwork each season and maintaining annualized inventories in States in which operations have begun are essential components of “Lose No Ground.”

In the early years of transition to annualized FIA, States were added to the program based on their willingness and ability to partner as test cases with stations. One reason that funding for the program has increased annually over the past 5 years is because Congress has seen increases in cost sharing and in-kind contributions from partners. As the program has grown and more States have been added, concerns have grown among the decreasing pool of States not yet annualized that they will be left behind with only an occasional periodic inventory. This concern has grown as the overall Federal budget has tightened to fund war and homeland-security-related needs. The long-term success of the FIA program is contingent on having all States included in the annualized program. The USDA Forest Service is committed to seeking the funds needed to implement annualized inventories in all States—“No State Left Behind.”

The FIA program is on a trajectory to achieve the funding level and coverage of all 50 States outlined in the 1998 FIA Strategic Plan. The plan has been very helpful for keeping program leaders, others inside the USDA Forest Service, and all FIA partners and clients focused on the shared goals and objectives for FIA. But now that achievement of the 1998 plan’s goals and objectives is imminent, the time to begin preparing a new FIA Strategic Plan is now.

### **Looking Ahead to 2007–12**

A new FIA Strategic Plan should aim at two broad goals. The first and primary goal is to consolidate the programmatic gains achieved in 1998–2006. This means keeping the annualized inventory program working smoothly in all 50 States and territories, meeting all deadlines for releasing compilations of annual data, and producing integrated analytical reports at 5-year intervals.

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The second goal is to create additional value for clients by augmenting the existing program with new features or levels of intensity. Some features may involve expanding coverage to fill critical information gaps and increasing spatial or temporal plot intensity. Others may involve creating new analyses and innovative uses of existing FIA data. In short, these twin goals emphasize better serving our core clientele by tuning up the existing program to make it better, faster, and cheaper, and adding a few carefully chosen new features to meet the most pressing emerging needs. Taken together, these actions will increase the value of the FIA program to a broader clientele.

To achieve the first goal, current business practices may need to change. For example, during the transition from periodic to annualized inventories, the task of writing data compilation software was undertaken both communally and individually. Station experts worked together to build common routines for collecting and compiling annualized field data. To compare the current situation with the most recent previous inventory (which consisted of periodic inventories of different types and ages, even within a single State and station), however, each station worked individually to build the routines to compare the past data with the present. When implementing annualized FIA in Kentucky, for example, the Southern Research Station had to work with data from the previous inventory created by the Northeastern Research Station using a different sampling scheme. Now that this transition is largely complete and a more consistent and common set of routines for compiling annualized FIA data exists, gaining additional efficiencies by further centralizing some of the data processing and compilation business processes may be possible. Additional advances from improving or reengineering other business practices may also be possible and should be explored. The improved internal discipline arising from having cross-station consistency as a core value for the new FIA program will make this change management task easier. Savings will be reinvested in improving the FIA program.

To achieve the second goal, an extended dialog is needed. Core clients remain an important source of support. A large number of potential clients need to be listened to, also. The following ideas have been presented in the past 2 years:

- Reduce the inventory cycles to 5 years everywhere.
- Move into urban areas to inventory all land.
- Broaden coverage of health issues, in particular to better characterize the impact of invasive species.
- Expand analyses to provide more information on issues for which forest vegetation structure and function are important influences, such as wildlife habitat quality.
- Intensify the grid on public and private land so that inventory data are more useful to resource managers at the forest management unit level.
- Expand the inventory to include rangeland and help characterize range condition, health, and trends.
- Broaden coverage of linear features, such as riparian zones, and link that data to the FIA grid.

Other concepts, including the following, have been expressed in less concrete terms:

- Take greater advantage of advanced satellite imagery, perhaps shifting some attributes from field plot collection as imagery provides more and more usable data.
- Develop faster, more accurate, more sophisticated change detection algorithms resulting in more timely and accurate assessments of land use/land cover dynamics.
- Develop more and better Web-based tools, such as adding more geospatial tools, so that users can customize their own analyses and make it easier for clients to build and populate their own unique data layers.
- Create better linkages between FIA data and pressing natural resource policy issues, such as fire and fuels analyses, fragmentation, sustainability reporting, certification, and other global issues.
- Build closer ties to the university community to take advantage of expertise for analyses and prototyping innovative techniques.
- Expand the use of FIA data in other parts of the USDA Forest Service for additional research and development and more State and Private Forestry programs and to improve the management of national forests and national grasslands.

All these suggestions have merit and would produce useful information for clients. All these suggestions also would

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increase program costs. None can be launched solely on cost savings wrung out of improved efficiencies in the ongoing program. All would require changes—sometimes radical changes—in the existing program to be accommodated. But after the past 6 years, the FIA program has come to embrace change as invigorating and as the only route to future success.

Over the next 18 months, the FIA National Program Leader and station FIA Program Managers will convene and facilitate a series of discussions with current and potential clients and USDA Forest Service leadership over the future foci of the FIA program for 2007–12. Regional and national user group meetings this year and next will be used to launch the dialog, and additional meetings will probably be needed to ensure that all points of view are heard and to build consensus on strategies. Moving the FIA program forward will be impossible without strong support among the entire FIA community of interest.

## Summary

The FIA program would not be in its current position without the strong, dedicated leadership of USDA Forest Service Research and Development employees and our partners. Together, we have accomplished great things in the past 5 years. Now is not the time to rest on our laurels or forswear further change. Rather, FIA's continued science mission is to help clients—all Americans—see their forests in new and different ways; to wisely protect, manage, and use them; and to leave them in better condition for our children and grandchildren. We cannot accomplish this mission alone, but we can accomplish it together.

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## Land-Base Changes in the United States: Long-Term Assessments of Forest Land Condition

Ralph J. Alig<sup>1</sup>

**Abstract.**—Forest land conditions affect the potential of U.S. forests to sustain a wide array of forest goods and environmental services (e.g., biodiversity) that society demands. Forest survey data collected by U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) units are being used in long-term assessments of U.S. forest land conditions at large scales. Resources Planning Act assessments, which employ a system of models, and FIA data enable a proactive examination of forest resources by projecting long-term changes in forest area and other forest ecosystem attributes in regional and national studies of forest sustainability. Forest land values provide informational signals on what amounts and types of forest land are likely and prospects for the provision of mixes of land-based goods and services. A key part of those land use changes, development of rural land, is related to population growth and affects forest land values, forest fragmentation, forest parcelization, and ownership changes. The FIA survey planning and related assessments would be enhanced by a unified framework, constructed at a scale that adequately serves all assessment areas, to analyze future land conditions.

### Introduction

Forests cover about one-third of the United States. These diverse land-based ecosystems provide a variety of habitats for wildlife; help to cleanse the air and water; supply timber, fuel wood, and other harvested products; serve as places for recreation; and provide other goods and environmental services. Long-term assessment of their condition and relations to changes in demographics and other socioeconomic factors is key in defining

policy questions and actions needed to sustain those services. Use of long-term databases, such as those compiled by the U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) program pertaining to changes in forest cover, will be integral in monitoring efforts and in supporting long-term projections of changes in forest land condition.

With changes in society, such as growth in population and increases in consumption, human-related pressures on the land base and forest land conditions are likely to increase. Across the United States, forest land conditions are altered by timber harvesting, fire management practices, conversion to other land uses, forest type transitions (including forest succession), recreation, and climate change. For example, wood use has increased by 40 percent since 1960 and is expected to rise by about 30 percent in the next four decades, which has implications for domestic timber harvest levels (Haynes 2003).

Projections of changes in forest land condition support long-range regional and national projections of future supply and demand for agricultural crops, animal products, forest products, recreation land, wildlife habitat, water use, and other landscape and environmental measures (see, e.g., USDA Forest Service 1988, 2001). An abundance of land is seen by some as a hallmark of the United States, and projections of developed area can aid decisionmaking as a forward-looking process in addressing questions such as whether adequate rural land will be available to support valued environmental goods and services in the future.

Periodic U.S. natural resource assessments mandated by the national (Forest and Rangeland Renewable) Resources Planning Act (RPA) of 1974 support USDA Forest Service strategic planning and policy analyses (USDA Forest Service 2001). RPA requires that decadal national assessments, with mid-decade updates, include an analysis of present and anticipated uses; demand for and supply of the renewable resources of forest,

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range, and other associated lands; and an emphasis on pertinent supply, demand, and price relationship trends. The 2000 RPA assessment provides a broad array of information about the Nation's forests and rangelands, including the current situation and prospective area changes over the next 50 years (Alig *et al.* 2003, Alig and Butler 2004). Related data illustrate the dynamics of our Nation's land base and how adjustments are likely to continue in the future. Projections of land use and forest cover changes provide inputs into a larger system of models that project timber resource conditions and harvests, wildlife habitat, and other natural resource conditions (USDA Forest Service 2001). These RPA assessments interface with international assessments (e.g., United Nations Conference on Environment and Development in 1992, Montreal Process set of sustainability criteria and indicators) and regional assessments, such as the study of the South's Fourth Forest (USDA Forest Service 1988) and an update by the Southern Forest Resources Assessment (Wear and Greis 2002). Information from the periodic RPA assessments can shed light on whether we can sustain increasing consumption of forest products and forest resource conditions.

This article has three parts. The first part discusses changes in macro forest land conditions, as evidenced by trends in land use, ownership, cover types, forest age, and proximity to concentrations of developed area. The second component focuses on large-scale modeling systems that use FIA data for investigating prospects for afforestation, reforestation, and deforestation (e.g., conversion to developed uses). The final section summarizes associated information and research needs, with an emphasis on environmental services and the link to human modifications of the environment.

## Land Use and Land Cover Changes—1953 to 2002

Examining historical trends provides guidance for identifying key factors that are likely to influence forest land conditions and associated natural resources in the future. The discussion of historical trends across time and space lays a foundation for subsequent discussion of projected changes in those same forest attributes. A major data source is the FIA survey program of

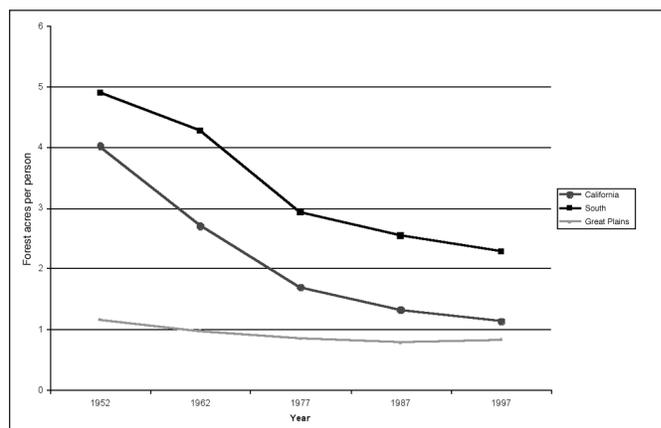
the USDA Forest Service. Regional FIA units have a long history of inventorying and monitoring the Nation's forests. This program originated with the McSweeney-McNary Forest Research Act of 1928 and has been in continuous operation in portions of the country ever since. During the 1970s, a national forest survey effort, having completed at least one inventory in most States, expanded its mission considerably by adding multiple resource inventories to the historical timber surveys. The FIA reports on status and trends in (1) forest area and location; (2) the species, size, and health of trees; (3) total tree growth, mortality, and removals by harvest; (4) wood production and utilization rates by various products; and (5) forest land ownership. The national FIA program Web site is <http://www.fia.fs.fed.us/>.

### Total Forest Area and Ownership

Key forest-related indicators at a national level are total forest area and trends by ownership. Between 1953 and 2002, the net change in U.S. forest area was a reduction of about 7 million acres, or 1 percent. Timberland area was reduced by a similar amount. Overall, forest area per person has declined notably since 1953 (fig. 1).

The largest forest ownership aggregate in the country, non-industrial private forest (NIPF) owners, experienced a 14-million-acre, or 5-percent, reduction in its timberland area. The largest concentration of NIPF owners is in the South, and their timberland area was reduced 6 percent. Most forest land development

Figure 1.—Amount of forest area per resident, for selected U.S. regions, 1952–1997. Source: Smith *et al.* 2004.



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occurs on land owned by NIPF owners. NIPF owners control the most U.S. timberland—58 percent (118 million ha) of the total. Even where public ownership predominates, NIPF ownership often accounts for land that provides critical habitat such as lowlands or riparian areas—e.g., NIPF ownership of Pacific Northwest land that is critical to threatened and endangered species (Bettinger and Alig 1996).

NIPF-owned timberland areas in the Pacific Northwest and Pacific Southwest, two other regions experiencing above-average growth rates in population and increases in developed area, are also decreasing. In the Pacific Northwest, NIPF timberland area dropped by 4.4 million acres, or 34 percent, between 1953 and 2002, while the corresponding reduction of NIPF timberland area in California (Pacific Southwest) has been 1.5 million acres, or 25 percent over the same period.

Land ownership can be an important determinant of how forest land is managed and the levels of investments in different practices (e.g., Alig *et al.* 1999). The relative proportions of private and public timberland have remained fairly stable since 1953, with about 29 percent of U.S. timberland in public ownership. In the private timberland group, the proportion of NIPF ownership dropped slightly, from 84 to 82 percent of total private ownership, between 1953 and 2002. Family forests are a large component of the NIPF ownership class; the number of family forest owners increased from 9.3 million in 1993 to 10.3 million in 2003, and these owners now control 42 percent of the Nation's forest land (Butler and Leatherberry 2004). The NIPF ownership class is the one most subject to land use changes, as evidenced by the 14-million-acre reduction in NIPF timberland area since 1953; in contrast, forest industry ownership increased by 7 million acres.

The long-term area increase in U.S. forest industry timberland peaked in 1987 at 70 million acres. Since then, U.S. forest industry timberland area has declined by 5 million acres, with some area reclassified as NIPF timberland because of a transition to institutional and other financial investors without timber-processing facilities. About half of that net reduction was in the Southeast, with a transition of land ownership from consolidated forest products companies to stand-alone financial ownership. Institutional investors currently hold about 8 percent of the

investable U.S. timberland (Wilent 2004). By the end of 2003, a Timber-Mart South newsletter reported that the top 10 timberland investment organizations (TIMOs) managed about 9 million acres of U.S. timberland, and some analysts predicted that TIMOs and other investor groups will purchase another 10 to 15 million acres in the next decade (Wilent 2004).

### **Forest Cover Types**

Forest cover is another important variable that affects wildlife habitat, timber supply, global climate change, water, recreation, and other forest ecosystem goods and services. Land cover is the observed biophysical cover on the Earth's surface, e.g., oak-hickory forest and grassland. Cover types are related to land use changes, with land use being the human-defined purpose of that land. For instance, lands can be defined as protected areas, forestry for timber products, plantations, row-crop agriculture, pastures, or human settlements. By examining historical trends of forest land area by forest cover type, we can better understand forest dynamics and their possible implications for sustainability.

The three largest historical cases of area changes for forest cover changes since 1953 have been in the eastern United States (Alig and Butler 2004). A key area change with timber supply implications is the more-than-tenfold increase in the planted pine area in the South since 1953, mostly on private lands. This growth illustrates that the largest recent impact on forest cover dynamics in the United States has been due to human influences, especially from changes in land management objectives. In the last half of the 20<sup>th</sup> century, application of intensive forestry, as with establishment of some pine plantations, has in some cases influenced the composition, structure, and ecological processes of forests. For instance, plantations and clearcutting have replaced natural regeneration and selective harvesting on some sites in the United States. An example is the conversion of naturally regenerated longleaf and slash pine stands with pine plantations, resulting in a 50-percent reduction in the area of the longleaf and slash pine type since 1953 (Smith *et al.* 2004). Intensive forestry on private timberland has generally reduced rotation lengths, which leads to more frequent regeneration opportunities and increases the probabilities of more forest cover changes.

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Along with the human-caused changes are the successional forces that led to a doubling of the area for maple-beech-birch type between 1953 and 2002 in the East. Two other hardwood types, oak-hickory and oak-pine, also increased more than 20 percent in area, gaining some of this area after timber harvests of other types. Although planted pine has increased in portions of the East, the hardwood types continue to dominate the area in this region.

Although softwood types dominate forest cover in the West, the largest area increase since 1953 has been the more than doubling of western hardwoods (Smith *et al.* 2004). In the softwood types, Douglas fir area has increased, sometimes at the expense of the western hemlock-Sitka spruce type. At higher elevations, the spruce fir cover type has almost doubled its area since 1953 due to successional forces. At a national scale, long-term data on forest cover changes are generally more available for private forests because FIA concentrated on private and State lands until recent decades when regional units assembled joint databases to include national forests and other lands.

### **Stand Age**

The FIA program classifies timberland by 10-year age class for even-aged stands, e.g., 0 to 9 years of age. The FIA surveys classified less than 5 percent of timberland as being uneven-aged (Smith *et al.* 2004). Timberland in the West tends to have older stands on average, with 4 percent of stands in the East being 100 years or older in comparison to 35 percent of western stands. The West also has close to 10 million timberland acres with stands that are 200 years old or older, or 7 percent of the total, in contrast to only about 50,000 acres in the East. Conversely, 22 percent of stands in the East are classified as being less than 20 years of age in contrast to 12 percent in the West.

Changes in age-class structure have various implications for timber inventory volumes and growth, with key differences on public versus private timberlands. For much of the country, we are seeing an aging of the forests and an accumulation of acres in the older seral stages as active timber production shifts to fewer acres. These changes are especially true in the North and West and particularly on public timberlands in the Pacific Northwest. In the South, by contrast, a shift from older hardwood

stands to younger softwood stands has occurred because of forest management decisions (Haynes 2003).

The combination of forest resource changes described above has been accompanied by an increase of almost a quarter trillion cubic feet (39 percent) in U.S. growing stock since 1953. The increases have been largely in the East, spread almost evenly between the North and South (Smith *et al.* 2004). Hardwoods experienced most of the increase. Since 1953, volumes have increased in all timber diameter classes below 25 inches (Smith *et al.* 2004); however, softwood volumes have decreased for classes above 25 inches whereas hardwood volumes have increased. The decline in large-diameter softwoods is due to harvesting of larger trees and the increased set-aside of timberland as reserved forest land (which reclassifies trees in these areas as nongrowing stock).

### **Forests in the Rural-Urban Continuum**

Forest land development increases the number of people who are living closer to remaining forest lands, in view of growing cities and other urban areas. A measure added in recent periodic FIA surveys has been the identification of forest lands by rural-urban continuum class. Based on nationwide rural-urban continuum classes (Smith *et al.* 2004), 13 percent of U.S. forest land now are located in major metropolitan counties, and 17 percent are in intermediate and small metropolitan counties and large towns, for a total of 30 percent of all U.S. forest land (Smith *et al.* 2004). Between 1997 and 2002, the forest area in major metropolitan areas increased by more than 5 million acres, or 5 percent, as developed areas in the United States expanded considerably.

The aforementioned descriptions of changes in the forest resource since 1953 provide a brief look at some of the natural resources and societal changes that are considered when projecting area changes for forest land and timberland by U.S. region. A method used increasingly in RPA assessments that uses FIA data is econometric modeling based on statistical methods used to quantify relationships between land uses and hypothesized determinants such as landowners' profit from land management (e.g., Kline and Alig 1999).

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## Systems Modeling: Projecting Forest Land Conditions

FIA data are used in the system of models employed for the periodic RPA assessments and related studies. For example, for the 2000 (fifth) RPA Timber Assessment (Haynes 2003), forest inventory data collected by the USDA Forest Service's FIA units were used to characterize current forest conditions and project forest inventories. A key model is the Timber Assessment Market Model (TAMM) for the solid wood products sector, which provides the linkage between product markets (solid wood and pulpwood) and the timber inventory (Adams and Haynes 1996). The North American Pulp and Paper Model (NAPAP) is a model of the paper and board sector, with detailed treatment of fiber supply (recycled, roundwood, and short-rotation woody crops) (Ince 1999). The Aggregate Timberland Assessment System (ATLAS) is a structure for projecting timber inventory over time based on FIA periodic data (Mills and Kincaid 1992). The AREACHANGE model explains the shifting of land between forest and nonforest uses and among forest types (Alig *et al.* 2003, Alig and Butler 2004). The RPA system of models is an example of a bioeconomic model because it combines representations of biological and economic processes.

In the RPA family of models, projecting land use changes requires FIA data pertaining to ownership, forest cover, site productivity, stand age, and removals. By using these and other data, the AREACHANGE model projects land use for the entire land base, including conversion of forest lands to urban and other built-up uses and land exchanges between forestry and agriculture. The information generated from the RPA family of models, in turn, is used for input into other models, such as the Forest and Agricultural Sector Optimization Model (FASOM). In FASOM, the forest sector is patterned in large part after the basic structures of the TAMM, NAPAP, ATLAS, and AREACHANGE models (Adams *et al.* 1996; Alig *et al.* 1998, 2002). The FASOM model endogenously allocates land between forest and agricultural use, such as in the case of afforestation. For example, in the two southern RPA regions, FASOM results indicated that the South Central region has relatively more potential for afforestation on agricultural land. Population growth in the Southeast has led to more deforestation

for developed uses in that region, based on projections by Alig *et al.* (2003, 2004), and the next section of this article indicates that forests are the largest source of developed land.

Highlights of the projections to 2050 by the 2000 RPA assessment include (1) U.S. consumption of forest products will continue to increase over the next 50 years, but the rate of increase will be slower than over the past 50 years; (2) most of the increase in the Nation's timber harvest will be in the East, especially on NIPF timberlands in the South; (3) softwood plantations will play an important role in future domestic timber harvest expansion, but such plantations will occupy less than 10 percent of U.S. timberland; (4) timber inventory volumes will increase—softwoods by 53 percent and hardwoods by 27 percent; (5) tree species composition will shift toward softwoods in the South and hardwoods in the North and remain largely unchanged in other regions; (6) the age-class structure of timberland managed on an even-age basis will be similar to current conditions on private lands but will shift toward older age classes on public lands; and (7) diversity indices that combine age class and forest type exhibit limited change over the projection period for the United States as a whole (Haynes 2003). In summary, based on broad-scale measures of forest resource conditions, the RPA assessment does not project dramatic changes in U.S. forest conditions over the next 50 years, even as timber harvest levels rise. Deforestation trends are examined more closely in the next section because this issue increasingly draws attention to current policy (e.g., open space concerns) and whether changes would be desirable.

### Deforestation Projections

In recent years, most U.S. deforestation has been due to conversion of forest land to developed uses, e.g., residential areas. The United States had a 34-percent increase in the amount of land devoted to urban and built-up uses between 1982 and 1997, according to the National Resources Inventory by the USDA (USDA NRCS 2001). The annual rate of conversion during the past 5 years of this period was more than 50 percent higher than during the previous 5 years. Forests in particular have been the largest source of land converted to developed uses in recent decades, with resulting impacts on forest cover and other ecological attributes. The largest increases in U.S. developed

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area between 1982 and 1997 were in the South, a key timber supply region. Between 1982 and 1997, 7 of the 10 States with the largest average annual additions of developed area were in the South. Expansion of developed area and urban sprawl in the South has been described as a major issue for future natural resource management, especially for the region's forests (Seelye 2001, Wear and Greis 2002). A recent FIA survey for North Carolina turned up a larger reduction in timberland area than in previous surveys. Wear and Greis (2002) project more than a 10-million-acre increase in developed area in the South over the next 25 years.

Development of rural land does not just result in direct conversion of forest land but can also involve forest fragmentation (Alig 2000, Butler *et al.* 2004), forest parcelization, and ownership changes. Development pressures can also add to uncertainty about how forest land will be managed if owners anticipate higher financial returns in an alternative use. Because forest land prices capture information regarding current as well as anticipated uses of land, land prices anticipate future development of forest land near urbanizing areas, casting a speculative shadow over timberland values (Wear and Newman 2004). With anticipated population and income growth, such dynamics could hold important implications for conditions of forest land and environmental benefits.

Projections suggest continued urban and other developed area expansion over the next 25 years, with the magnitude of increase differing by region (Alig *et al.* 2004). For nonfederal land in the contiguous 48 states, the U.S. developed area is projected to increase by 79 percent, raising the proportion of the total developed land base from 5.2 to 9.2 percent. Because much of the growth is expected in areas relatively stressed with respect to human-environment interactions, such as some coastal counties, implications for landscape and urban planning include potential impacts on sensitive watersheds, riparian areas, wildlife habitat, and water supplies. The projected developed and built-up area of about 175 million acres in 2025 represents an area equal to 38 percent of the current U.S. cropland base, or 23 percent of the current U.S. forest land base.

When examining land use dynamics, the many pathways by which land use can change warrant examining both net and gross area changes for major land uses. The total or gross area shifts involving U.S. forests are relatively large compared to net estimates. Gross area changes involving U.S. forests totaled about 50 million acres between 1982 and 1997, an order of magnitude greater than the net change of 4 million acres. Movement of land between forestry and agriculture in the last two decades resulted in net gains to forestry that have offset forest conversion to urban and developed uses in area terms. The conditions of forested acres entering and exiting the forest land base, however, can be quite different; entering acres may have young trees, such as for old-field natural succession cases, whereas exiting acres often contain large trees before conversion to developed uses. Concern about the attributes of exiting or entering forested acres was heightened in the 1990s when the rate of development increased, with about 1 million acres of forests converted to developed uses per year (USDA NRCS 2001).

The deforestation projections do not include remaining forest land that over time has added more people per square mile but not enough to be reclassified as nonforest land. Within current FIA definitions, the major effective use of forest land could conceivably shift to a nontimber use as housing density per acre increases, but the shift may not be enough to reclassify the land as nonforest. This point is also relevant later in this article in the discussion of forest parcelization. Empirical studies using FIA data are investigating thresholds at which the actual use effectively shifts (e.g., Kline *et al.* 2004b).

### **Implications for Forest Land Values**

Implications of the projected increases in developed area for forestry extend to effects on forest land values. Land prices embody information on relative valuations by different sectors of the economy. For example, valuation of land currently in forest uses in some areas is strongly influenced by trends in developed areas (e.g., Wear and Newman 2004). Land values for developed uses typically exceed those for rural uses by a substantial amount (Alig and Plantinga 2004). Agricultural values are usually second to developed uses in potential value, and they are often influenced by development potential. With rural land uses subject to increasing conversion pressure, open

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space concerns have heightened. The earliest significant U.S. efforts to preserve open space involved preserving and restoring publicly owned forests and parks at national and State levels. These efforts were inspired by public concern for rapid loss of forests to agriculture and logging in the late 19<sup>th</sup> century and the desire to protect timber and water resources and lands of extraordinary beauty and uniqueness. Since then, public concern for land use change has evolved to recognize the contribution of open space to our day-to-day quality of life—its recreation, aesthetic, ecological, and resource protection benefits.

Forest land values can differ in a variety of geographic, biological, regulatory, economic, and social situations and are important in determining how much land is allocated to forest use. Given that complex of factors, forest use valuation is increasingly becoming more complicated, as is our economy, by overlays of land use zoning, environmental laws, forest practices regulation, site-specific environmental considerations, and recognition of forest resource values other than timber. For example, the State of Oregon is currently dealing with land value issues as part of its response to Ballot Measure 37. This ballot measure may have substantial impacts on the State's land use planning, which includes protecting forest and agricultural lands in certain zones. The measure was promoted as a land valuation supplement to earlier land use planning that focused on biophysical measures. Approved by Oregon voters on November 2, 2004, Measure 37 allows a landowner to apply for relief from land use rules created since the landowner's family acquired a property. If the landowner shows that the property value has been harmed, the government responsible for the rule must waive it or pay for the loss of value. Other States in the West are monitoring the Oregon case because the West has experienced larger than average population growth, and a recent FIA survey in western Washington estimated that conversion of forest land to developed uses had increased compared with the previous survey period.

The Oregon case illustrates that people differ in the values that they place on environmental, economic, and social aspects of forests. This affects the social valuation and is in contrast to the private cost of providing goods and services that others may value from private forest land. An example is that many forest lands and open spaces include social values—ecological, scenic,

recreation, and resource protection values that are typically not reflected in market prices for land when some forest land is developed (Kline *et al.* 2004a). For open space policy, one needs to understand social values in the context of forest land market values and the economic rationale and impetus for public and private efforts to protect forest land as open space. Kline and Alig (1999) used FIA data to investigate the effectiveness of Oregon's land use law, and current research is examining whether forest land values can reveal what it may cost to pursue different sustainability options if land easements, purchases, or rentals are desired. The land values reveal what people are actually willing to pay for a bundle of rights necessary to gain access to land that can provide goods and services for a certain period. Changing perceptions about forest land mirror those in farmland preservation. National interest in preserving farmland arose in the 1970s from concerns about rapid loss of farmland to development and the supposed threat to food security and agricultural viability. These concerns led to the gradual and nearly nationwide implementation of local, State, and Federal farmland preservation programs (Kline *et al.* 2004a). More recently, recognition has grown for the environmental amenities and the social values of farmland and the role they play in motivating public support for preserving farmland. Incorporating land-based values into farmland protection policies and programs helps to ensure that the public is getting what it desires from preserved farmland. Similar efforts may now be needed for forest lands to ensure that public and private open space protection efforts are tailored to provide the social values desired from forest lands.

Land-base changes can affect many goods and services, including those for historically nontraditional forest-based goods and environmental services such as biodiversity, which is increasingly used as an ecosystem indicator. Human-environment impacts that affect biodiversity can vary across space and time, such as physical fragmentation of forest cover from land use changes, which can affect natural resources in a variety of ways. For example, development of rural land may cause fragmentation of wildlife habitat. A landscape that is optimal for a private owner can depart from a socially optimal landscape that reflects society's preferences for public goods associated with interior forest parcels. Future policy-related research can examine land

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use shifts for parcels to identify optimal ways for reducing forest fragmentation. Spatial configurations make this complex, however, in that benefits of converting (or retaining) a parcel will depend on the land uses of the neighboring parcels as well as on other parcels affected by the policy.

## Future Directions

Forests are increasingly subjected to human-caused modifications and stresses. For the FIA program, one challenge is to increasingly link forest resource data to socioeconomic data, such as characteristics of forest land owners. This challenge reflects the large diversity of data needed to address policy questions (e.g., well-being of natural-resource-dependent communities) that arise given increased attention to sustainability and activities associated with the environment, economy, and societal institutions. Much discussion in forest policy circles today is about forest sustainability (Alig and Haynes 2001), which seems to be part of a larger societal concern about quality of life and the long-term capability of land to provide goods and services that we as a society demand. Issues for land use and land cover monitoring and assessment include consistent coverage across the entire land base. Analogous to the snapshot of land use information by USDA's National Resources Inventory, land cover modeling would benefit from periodic nationwide estimates of changes in forest cover, e.g., National Land Cover Data mapping project. Field-based observations are also needed to provide complementary data such as land ownership and site quality.

Monitoring changes in ownership of forests would also be useful because sales and acquisitions of forest lands reflect active market forces, globalization, and consolidation effects on the forest sector. The forest industry is increasingly viewing its forests as strategic financial assets (Wilent 2004). Fragmentation of private lands and expected resulting changes from conversion of forest to developed uses are being assessed in an ongoing "Forests on the Edge" national project (Stein 2004). Breaking up of ownerships into several smaller ownerships—parcelization—can also have profound impacts on the economics of farming or forestry, even when land is not physically altered in any major way.

Trends in population density warrant further study for different classes of rural and urban land (Alig 2000). The United States had about 80 people per square mile of land in 1999 (U.S. Department of Commerce, Census Bureau 2001). This population density compares to about 5 people per square mile in 1790 and a world average of more than 100 people per square mile in 1999 (United Nations 2002). More people on the landscape include those in rural areas with attractive recreational land and aesthetic amenities, often involving forests. People migration because of amenity attractions is related to concerns about changes in quality of life. Such demographic changes increase the size of the wildland-urban interface, exacerbating wildfire threats to structures and people.

Human demands for forests will escalate as populations grow and personal incomes increase, challenging land managers to provide for a diverse array of societal needs, including ecological (e.g., biodiversity), economic, and social needs. In addition to substantial demand for environmental services such as biodiversity, water quality improvement, and carbon sequestration, there is growing interest in spiritual values associated with forests and in forests' sustainable use and restoration after certain disturbances. Related research is needed to help dovetail design of incentives and assistance for private landowners to promote conservation objectives and other social values while meeting their personal objectives. NIPF owners will increasingly experience pressures to produce multiple goods and services from their forest lands, often in the face of mounting pressure from development. Insights might be gained by reviewing forest survey methods and analyses in other countries with large NIPF components, such as Finland. Spatial and temporal scales of inquiry are important, too, in that specific issues can emerge at particular scales. A growing population will affect choices in the United States, which has a rich legacy of forests managed by a variety of individuals, corporations, governments, and others for many goods and services (Beuter and Alig 2004).

Advances in land use analyses will likely rest in part on the continued improvement of spatial databases, including spatial socioeconomic data, and improvements in spatial econometric methods to support empirical data analyses. Tradeoffs must be

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considered when assessing the costs and benefits associated with providing more spatial detail, as well as tradeoffs and costs in the FIA transition from periodic to annual surveys. Related issues are privacy and disclosure considerations for private owners of forest lands in light of increasing availability of spatial data. Along with improved databases, monitoring of developed area trends, associated investment in infrastructure (e.g., transportation networks and nodes), and related socioeconomic factors will be important in facilitating updated projections of U.S. developed area. Monitoring such changes will be important, as will be defining key policy-relevant questions that can lead to effective land use and land cover monitoring and assessments and land management.

Given the expected growth in U.S. population and changes in economic activity, a key question is how society can make positive progress toward “sustainability” in the face of needing more developed land to serve more people in the future. Agreement among stakeholders of the forests when it comes to sustainable use is likely to be a contentious issue because of the inherent tensions and conflicts. Location-specific balancing of interests may be possible, but overall progress toward such goals may rest on a more integrated approach for describing the complex interplay between human activity and the environment. To help evaluate progress, we need a useful definition of sustainability along with measurable indicators that fundamentally reflect the long-term ecological, economic, and social well-being as they relate to alternative uses of land. Data collection by FIA units could play an important role, e.g., by monitoring impacts of global climate change on future forest conditions such as forest type and biodiversity changes.

A major complication in past FIA survey planning, RPA assessments, and global climate change assessments has been the lack of a unified view of future land conditions at a scale that serves all these assessment areas adequately. Attaining the ideal unification is a substantial undertaking, and this unification could be assisted up front by an assessment of common information needs. A modeling system that can project land base conditions for forest ecosystems could provide a thorough and unified description of anticipated change in the extent, structure, and condition of the Nation’s forests at useful regional and sub-

regional scales. At the same time, such a system could augment economic measures, which would be useful when investigating changes in land markets and analyzing trends in land values.

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## Estimation of U.S. Timber Harvest Using Roundwood Equivalents

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**Abstract.**—This report details the procedure used to estimate the roundwood products portion of U.S. annual timber harvest levels by using roundwood equivalents. National-level U.S. forest products data published by trade associations and State and Federal Government organizations were used to estimate the roundwood equivalent of national roundwood products production. The procedure for estimating roundwood equivalent of roundwood products is to calculate the “roundwood equivalent” of solid wood products using recovery factors estimated from mill studies over the years. The procedure for estimating roundwood equivalent of products provides a simple technique for estimating the major portion of national timber harvest levels that is less expensive than conducting surveys and can be done on an annual basis. This technique provides a benchmark that can be used in conjunction with the Forest Inventory and Analysis survey approach, which helps ensure the accuracy of both methods. These national harvest levels were estimated by working backwards from U.S. national timber products production data using lumber recovery factors to derive the roundwood equivalent of harvest.

### Introduction

Federal law requires that the U.S. Department of Agriculture (USDA) maintain a current analysis of the demand and supply of resources from forest land and rangelands. Specifically, the Renewable Resources Planning Act (RPA) of 1976 and the Forest and Rangeland Renewable Resources Research Act of 1978 require development of periodic programs and assessments. The Research Act directs the Secretary of Agriculture to make and keep a comprehensive survey and analysis of present and

prospective conditions of and requirements for renewable resources of forest and range lands of the United States. The compilation of roundwood equivalents of harvest, defined as an estimate of the solid volume (i.e., total wood content) of a processed log in cubic units derived by multiplying the final products by product recovery factors, are computed in a spreadsheet. In the roundwood equivalent spreadsheet, the four major groupings of industrial roundwood uses (under headings “Industrial roundwood used for”) are (1) lumber, (2) plywood and veneer products, (3) pulpwood-based products, and (4) other. Each group contains more specific subcategories of products, which encompass all primary industrial wood and wood fiber products. The subcategories for lumber are softwood (SW) lumber, hardwood (HW) lumber, and pallets (produced at sawmills); plywood and veneer products are SW plywood, HW plywood, and laminated veneer lumber (LVL); pulpwood-based products are oriented strandboard (OSB), particleboard, hardboard, medium-density fiberboard (MDF) and insulation board, and pulp, paper and paperboard. In the pulpwood-based products category, the spreadsheet accounts only for estimated roundwood inputs, not wood residue inputs. Wood residue inputs are included as part of roundwood initially sent to sawmills or other mills that produce residue. The “other” category is composed of posts, poles, piling, and miscellaneous products. Apart from these categories, log and chip trade and fuel wood are also accounted for. The intent of the roundwood equivalent estimation is to calculate roundwood harvest on an annual basis or the roundwood equivalent of logs that actually get on the logging truck. This estimate of timber use differs from total harvest and removals from growing stock because the roundwood equivalent estimation does not include logging residues, which are left in the woods, or other removals, such as land clearing for development that may exclude timber output.

The procedure for estimating the roundwood equivalent of harvest is to back out the roundwood equivalent of products using recovery factors estimated from mill studies over the years.

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Table 1.—*Production of timber products, by major product, various years, 1965–2002 (million cubic feet, roundwood equivalent).<sup>a</sup>*

	1965	1970	1976	1986	1988	1991	1996	2002
All products	12,276	14,702	13,580	18,328	18,736	18,823	17,268	16
Industrial roundwood use								
Total	11,230	13,287	12,102	14,644	15,618	15,187	15,344	14,963
Lumber	6,233	6,511	6,026	7,105	7,667	7,039	6,975	7,347
Plywood and veneer	1,070	1,197	1,466	1,598	1,598	1,267	1,281	1,067
Pulpwood-based products	3,176	4,488	3,715	4,881	5,075	5,397	5,908	5,699
Other industrial products <sup>b</sup>	560	652	375	475	510	551	342	317
Log exports <sup>d</sup>	191	438	520	585	767	602	422	388
Pulpwood chip exports <sup>c</sup>	7	150	245	151	218	332	416	189
Fuel wood	1,038	1,265	1,232	3,533	2,901	3,636	1,924	1,520

<sup>a</sup> Howard (2003), 21.

<sup>b</sup> Includes cooperage logs, poles and piling, fence posts, hewn ties, round mine timbers, box bolts, excelsior bolts, chemical wood, shingle bolts, and miscellaneous items.

<sup>c</sup> Before 1989, pulpwood chips were not included in total production.

<sup>d</sup> Before 2000, pulpwood logs were not included in logs.

The timber harvest or roundwood equivalents associated with production, trade, and consumption of all wood-based products were computed for the entire United States from 1965 to 2002 (Howard 2003) based on product output data and average roundwood input coefficients by product category. Since 1991—the peak roundwood production year in the United States—when the production of roundwood was 18.8 billion ft<sup>3</sup>, roundwood harvest has declined steadily to 16.5 billion ft<sup>3</sup> in 2002 (table 1).

The Timber Demand and Technology Assessment Research Work Unit at the Forest Products Laboratory (FPL) has as part of its mission the development of historical U.S. timber production statistics. Historical statistics are developed to support USDA Forest Service RPA objectives, which are in part to produce U.S. timber harvest trends. The Timber Assessment Market Model (TAMM) (Adams and Haynes 1996) was developed and is used to produce national assessments of supply and demand trends for timber in support of RPA objectives. FPL's historical timber production statistics are used by TAMM to create a plausible baseline projection of future changes in the Nation's demand for timber products and in the domestic resource that supplies a substantial part of our timber requirements. Annual roundwood equivalent of harvest estimations is used to substantiate the accuracy of timber product output (TPO) for years in which TPO harvest data are published. Also, the 1998 Farm Bill charged the national FIA program with developing an annualized forest

inventory so that users would have current data for their planning and decisionmaking processes. The FPL procedure for estimating annual harvest helps accomplish the FIA program goal established in the Farm Bill by providing a complementary method for making reasonable annual national harvest estimates

## Methods

Each of the four major product categories has a subset of several primary product categories for a total of 15 product categories that enter into the computation for roundwood equivalent of harvest (table 2). The production data for each of the 15 product categories were collected from industry trade associations and government agencies. The USDA Forest Service has developed and kept up to date appropriate statistical series on timber, wood, and fiber products production since its inception (Johnson 2001). These statistics extend and complement data found in other RPA assessment reports (Haynes 2003). The 15 product categories are the basis for estimating the roundwood equivalent of harvest, which contributes to satisfying the RPA requirement by providing the historical data needed for long-term RPA projections.

Table 3 shows an example of roundwood equivalent calculation for lumber (2002 data) that illustrates the procedure for using product recovery factors and the computation of the roundwood

Table 2.—U.S. annual industrial wood product production, various years, 1965–2002.<sup>a</sup>

Product	1965	1970	1976	1986	1988	1991	1996	2002
Softwood plywood	12,447	14,340	18,440	22,118	22,599	18,652	19,181	15,200
Oriented strandboard	NA	NA	NA	3,513	4,604	5,613	9,314	13,426
Laminated veneer lumber	NA	NA	NA	8	11	16	32	56
Hardwood plywood and veneer	2,049	1,796	1,083	1,390	1,552	1,496	1,784	2,096
Softwood lumber	29,295	27,530	30,600	35,273	38,130	33,161	33,266	35,831
Hardwood lumber	9,440	8,330	7,977	10,477	11,741	11,168	12,488	11,750
Lumber made at pallet plants	171	247	383	721	876	1,005	660	735
Particleboard	753	1,731	3,189	3,603	3,829	3,772	4,459	4,414
Hardboard	2,921	4,384	6,785	5,822	5,118	4,895	5,280	2,919
Medium-density fiberboard	75	127	280	781	939	958	1,246	1,621
Pulp, paper, and board	40,489	48,719	54,993	70,905	76,587	79,427	90,381	89,687
Other industrial products	560	652	375	475	510	551	342	317
Insulating board	3,362	3,194	3,407	2,194	2,340	2,323	2,335	2,335
Log exports	1,195	2,741	3,250	3,656	4,798	3,761	2,636	2,428
Fuel wood	1,038	1,265	1,232	3,533	2,901	3,636	1,924	1,520

NA = Not available. <sup>a</sup> Howard (2003), 29.

Table 3.—Roundwood equivalent calculation for lumber example.

Product	Production level	Factor to convert production to roundwood requirement	Roundwood equivalent (million ft <sup>3</sup> )
Softwood			
Lumber	36,400 x 10 <sup>6</sup> board feet	6.952 board feet/ft <sup>3</sup>	5,236
Pallets	40 x 10 <sup>6</sup> pallets	0.18 ft <sup>3</sup> /pallet	7.2
Hardwood			
Lumber	11,800 x 10 <sup>6</sup> board feet	5.74 board feet/ft <sup>3</sup>	2,056
Pallets	401 x 10 <sup>6</sup> pallets	0.12 ft <sup>3</sup> /pallet	48.12
			7,347.3

Table 4.—Product recovery factors, various years, 1965–2002.<sup>a</sup>

Product	Conversion factor units	1965	1970	1976	1986	1988	1991	1996	2002
Softwood plywood	ft <sup>3</sup> /ft <sup>2</sup>	0.0753	0.0753	0.0757	0.0676	0.0656	0.0617	0.0586	0.0562
Hardwood plywood and veneer	ft <sup>3</sup> /ft <sup>2</sup>	0.0651	0.0651	0.0651	0.0613	0.0598	0.0567	0.0544	0.0524
Lumber									
Softwood lumber	ft <sup>3</sup> /board foot	6.400	6.400	6.438	6.734	6.828	6.952	6.952	6.952
Hardwood lumber	ft <sup>3</sup> /board foot	5.74	5.74	5.74	5.74	5.74	5.74	5.74	5.74
Lumber made at pallet plants									
Softwood		0.35	0.35	0.35	0.35	0.31	0.25	0.18	0.18
Hardwood		—	—	—	—	—	—	—	—
Laminated veneer lumber	ft <sup>3</sup> /ft <sup>3</sup>	NA	NA	NA	2.16	2.10	1.98	1.87	1.80
Oriented strandboard	ft <sup>3</sup> /ft <sup>2</sup>	NA	NA	NA	0.06	0.06	0.05	0.05	0.05
Particleboard	ft <sup>3</sup> /ft <sup>2</sup>	0.0083	0.0083	0.0083	0.0085	0.0086	0.0086	0.0088	0.0088
Hardboard	ft <sup>3</sup> /ft <sup>2</sup>	0.0012	0.0012	0.0012	0.0013	0.0013	0.0013	0.0013	0.0013
Medium-density fiberboard	ft <sup>3</sup> /ft <sup>2</sup>	0.0075	0.0075	0.0075	0.0077	0.0077	0.0078	0.0078	0.0078
Insulating board	ft <sup>3</sup> /ft <sup>2</sup>	0.00495	0.00495	0.00495	0.00506	0.00510	0.00513	0.00515	0.00515
Log exports	ft <sup>3</sup> /board foot	0.02832	0.02832	0.02832	0.02832	0.02832	0.02832	0.02832	0.02832
Other industrial products		1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Pulpwood									
Softwood	ft <sup>3</sup> /ton	81	81	81	84	84	84	84	84
Hardwood	ft <sup>3</sup> /ton	78	78	78	78	78	78	78	78

NA = Not available. <sup>a</sup> Unpublished TAMM data.

equivalent of lumber. Note that this procedure changes slightly depending on the product that roundwood equivalents are being estimated for. Typically the difference is whether to multiply or divide the entity in the product column by the recovery factor.

The FPL roundwood equivalent estimates of harvest for all solid wood products (e.g., lumber, plywood, OSB) are based on product recovery factors (table 4). Product recovery factors are cubic feet volume measurements of roundwood produced per unit of solid wood product input (see table 2 for units). Some solid wood products in the FPL system have both SW and HW components, such as HW plywood. HW plywood is sometimes constructed with SW material as a core. In such cases, a roundwood proportion is used to estimate the roundwood equivalent of HW plywood in conjunction with the product recovery factor. The product recovery factors change over time to reflect changes in timber characteristics such as size, taper, and defect. Policy restrictions governing harvests, especially from public lands, have contributed to a difference in the average characteristics of harvested timber and timber making up the merchantable growing stock inventory. Changes in product recovery factors over time also reflect mill technology changes and market impacts (Spelter 2002). Fuel wood estimates for all but the most recent years are from TPO estimates. Preliminary estimates are made for recent years where TPO data are not available based on the U.S. Department of Energy (DOE) restricted energy consumption survey.

## Findings

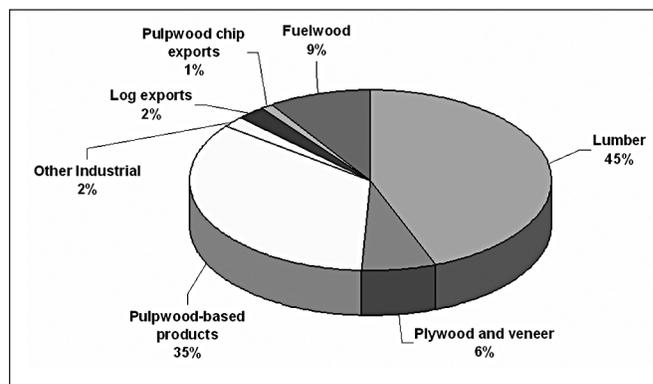
U. S. harvest (or roundwood equivalent of production) decreased to 16.5 billion ft<sup>3</sup> in 2002, down slightly from 16.6 billion ft<sup>3</sup> a year earlier. The roundwood harvest peaked in 1991, when industrial roundwood production was 18.8 billion ft<sup>3</sup> (table 1). Lumber and pulpwood-based products by far make up the largest share (80 percent) of roundwood use (fig. 1). The 2002 level for timber harvest was estimated by converting the 15 solid wood products to cubic feet of roundwood using product recovery factors. Since 1986, the largest decline by far was in fuel wood production (- 2 billion ft<sup>3</sup>), followed by plywood (- 0.5 billion ft<sup>3</sup>); the largest gains were in pulpwood production (+ 0.8 billion ft<sup>3</sup>).

Fuel wood is the only product for which product recovery factors are not used to estimate roundwood equivalents. An indexing procedure is used to estimate and update the fuel wood component of estimated timber harvest. Historical TPO estimates are indexed to the DOE residential fuel wood use estimates starting in the base year, 1990. Linear interpolation between DOE residential fuel wood survey years is done to provide TPO household fuel wood use estimates. Timber harvest, or the roundwood equivalents associated with production and trade, is therefore the summation of all wood-based products for the entire United States.

Roundwood equivalents plus the estimate for fuel wood are added and then compared with USDA Forest Service TPO estimates of annual U.S. timber harvest made at six points in time since 1952, and roundwood equivalents are evaluated as a proxy for annual timber harvest data in years when actual data are not available.

The lumber and engineered wood products sectors are the main contributors to the current harvest level. An estimated 48.0 billion board feet of SW lumber plus HWs were produced in the United States in 2002 (table 2). Lumber production climbed upward from 1965 to a peak in 1988 but then declined. The production of saw logs used in the domestic manufacture of lumber rose slightly in 2002 to 7.3 billion ft<sup>3</sup> (table 1), representing about 44 percent of total industrial roundwood production. Of the total timber harvested, 32 percent were processed to produce SW lumber, and 12 percent were processed to produce HW lumber.

Figure 1.—Industrial roundwood use, 2002 (Howard 2003).



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SW plywood production in 2002 was estimated at 15.2 billion ft<sup>2</sup> (3/8-in basis) based on data published by APA—The Engineered Wood Association (table 2). This figure represented about 9 percent of SW industrial roundwood production in 2002 (table 1). HW plywood production had fallen annually for three straight years to an estimated 2.0 billion ft<sup>2</sup> in 2002 (3/8-in basis). This 2002 level of production accounted for 2 percent of total HW industrial roundwood use.

Included in the pulpwood-based products category, total wood pulp, paper, and board production in U.S. mills in 2002 was estimated at 89.7 million tons based on data published by the American Forest and Paper Association (table 2). This excludes dissolving pulp and pulp produced for hardboard, MDF, and related products. In addition, OSB production was 13.4 million ft<sup>2</sup> (3/8-in basis), which represented 5.7 billion ft<sup>3</sup> of roundwood, or 35 percent of total industrial roundwood use (table 1).

According to estimates of the National Particleboard Association (table 2), production of particleboard in 2002 totaled 4.4 billion ft<sup>2</sup> (3/4-in basis). Production of MDF in 2002 was 1.6 billion ft<sup>2</sup> (3/4-in basis). Hardboard production in 2002 was estimated to be 2.9 billion ft<sup>2</sup> (1/8-in basis). Production of insulation board in 2002 was 2.3 billion ft<sup>2</sup> (1/2-in basis), or 857,000 tons. These subcategories are components of the pulpwood-based products category

Engineered wood products such as glulam, I-joists, and LVL are relatively new to the market, and production levels for these products are forecast to increase steadily. During 2002, glulam production was 321 million board feet, LVL production was 56 million ft<sup>3</sup>, and I-joist production was 756 million linear feet. Glulam and I-joists roundwood usage currently are not accounted for in terms of roundwood use, whereas LVL production is accounted for in the plywood and veneer category.

Total SW log exports decreased 10.1 percent during 2002. SW log exports from the Western United States continued a downward trend as Douglas fir log exports declined 3.8 percent in 2002. Log exports make up 2 percent of industrial roundwood use (fig. 1).

Production of miscellaneous or other industrial roundwood products, which includes cooperage logs, poles and piling, fence posts, mine timbers, and an assortment of other products such as hewn ties and box bolts, is estimated at 317 million ft<sup>3</sup> in 2002. This category represented 2 percent of industrial roundwood use, less than half the amount used in 1986. Production of round fuel wood in 2002 is estimated at 1.5 billion ft<sup>3</sup>.

## Conclusions

This effort to produce a complementary method for estimating annual harvest helps accomplish the goal set forward in the 1998 Farm Bill. The national FIA program was charged with developing an annualized forest inventory so that users would have current data for their planning and decisionmaking processes. The production of TPO estimates helps accomplish RPA national timber assessment objectives. The two concepts of timber harvest associated with roundwood products and roundwood equivalents of industrial timber removals are comparable. They are compared by the use of product recovery rates, which differ for each of the 15 solid wood product classes. The product recovery rates also change over time to reflect changes in the timber resource characteristics, technology, and markets. Shifting patterns of timber harvests have contributed to a change in the average characteristics of harvested timber and timber that make up the merchantable growing-stock inventory. Fuel wood is the only commodity for which product recovery rates are not used. Instead, an indexing procedure, which uses DOE estimates, is used to calculate household fuel wood use. Lumber is the largest product category for roundwood use, followed closely by pulpwood-based products. Precise breakdowns by species or ownership are not possible using the roundwood equivalent approach, even at the national level. This approach was specifically designed to perform aggregate national estimates.

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## Broad-Scale Assessment of Fuel Treatment Opportunities

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**Abstract.**—The Forest Inventory and Analysis (FIA) program has produced estimates of the extent and composition of the Nation's forests for several decades. FIA data have been used with a flexible silvicultural thinning option, a fire hazard model for preharvest and postharvest fire hazard assessment, a harvest economics model, and geospatial data to produce a Web-based tool to assess fuel treatment opportunities at a strategic level. This tool, the Fuel Treatment Evaluator, was used in this study to show how to identify potential fuel treatment hotspots in the Western United States.

### Introduction

Decades of fire prevention and suppression efforts in the Western United States have led to an accumulation of fuels that are increasing the risk of catastrophic fire. In the past, fire-adapted forests had relatively open canopies and small amounts of ladder fuels due to frequent low-intensity fires. Today, due to fire prevention and suppression efforts, canopies and vertical structure are more closed. Although most fires continue to be low-intensity ground fires, an increase in the incidence of high-intensity crown fires has occurred. Crown fires are much more difficult and expensive to control, cause greater ecological disturbance, and impose a higher risk to life and property than ground fires.

Concern over increased fire hazard has led to research at local and regional levels. The Pacific Northwest Research Station developed an analytical tool called BioSum that uses forest inventory data to determine areas at risk and subsequent fuel

treatment opportunities (Fried *et al.* 2003). BioSum intensively examines a multicounty project area. With the development of a nationwide forest inventory database in 2002 (Miles *et al.* 2004), it became possible to take a more strategic, albeit less intensive, multiState approach to fire hazard assessment.

In April 2003, a white paper entitled "A Strategic Assessment of Forest Biomass and Fuel Reduction Treatments in Western States" (USDA Forest Service 2005) was released. This "west-wide biomass assessment" combined forest inventory data with a coarse-scale current fire condition class map (Schmidt *et al.* 2002) to identify areas at risk and the amount of biomass on those areas. Potential removal volumes were identified based on selective removal prescriptions using the stand density index (SDI) criterion (Reineke 1933).

As a result of the westwide biomass assessment, it was estimated that in the 15 western States at least 28 million acres of forest could benefit from some type of mechanical treatment to reduce hazardous fuel loading.

This article describes enhancements to the methods used in the westwide biomass assessment. Both the silvicultural thinning prescriptions and the fire hazard assessment were enhanced. Additional information is developed on harvest costs and the area and amount of thinning that occurs in the wildland-urban interface (WUI) (Radeloff *et al.* 2005).

### Methodology

This analysis used a Web-based tool called the Fuel Treatment Evaluator (FTE), available at [www.ncrs2.fs.fed.us/4801/fiadb/fuelreatment/fuelreatmentwc.asp](http://www.ncrs2.fs.fed.us/4801/fiadb/fuelreatment/fuelreatmentwc.asp). The FTE combines forest inventory data with other information to aid in the development

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of fuel reduction alternatives to reduce fire hazard. Other sources of information include a silvicultural prescription for thinning based on SDI, a method for estimating fire hazard (before and after treatment) based on stand and tree characteristics, a method for calculating harvest costs/benefits based on stand and tree characteristics, and geospatial information such as current fire condition class and WUI.

### **Forest Inventory Data**

The FTE program currently uses data from the 2002 Resources Planning Act (RPA) database. (For a complete listing of data sources for the 2002 RPA database, see Smith *et al.* 2004).

The FTE can be used to generate files in Forest Vegetation Simulator (FVS) format for preharvest and postharvest conditions (Dixon 2004). These data could then be run through the Fuels and Fire Extension component of FVS to project future fire hazard (Reinhardt and Crookston 2003). Projecting future fire hazard is beyond the scope of this analysis.

### **Flexible SDI Thinning Prescription**

SDI is a long-established, science-based, forest stocking guide that can be adapted to uneven-aged forests (Long and Daniel 1990) using data from broad-scale inventories. SDI measures can be used to identify areas or stands that would benefit from biomass reduction.

In the westwide biomass assessment, a stand was thinned until it was minimally fully stocked (30 percent of the maximum SDI for that forest type and ecoregion). To accomplish this, the target SDI was evenly divided among diameter classes in an inventory plot. The excess number of trees in each diameter class is the harvest yield for the treatment. This method identifies trees in each diameter class that may be available for fuel-reduction removals while ensuring sufficient “leave” trees to maintain site occupancy (Vissage and Miles 2003).

One problem associated with the apportionment of desired SDI values across diameter classes in multi- or uneven-aged forests was the inability to systematically adjust the slope of the desired stocking curve. Basically, adjusting the desired percentage of maximum SDI desired after thinning raised or lowered the

stocking curve but did not change its shape. This adjustment resulted in large numbers of small trees being retained regardless of the percent of maximum SDI prescribed, which has been a major criticism of using SDI-based stocking control for fuels treatment biomass estimates.

As a result of this criticism, a flex factor option was added to the FTE to proportionally reduce the amount of SDI assigned to successively smaller diameter at breast height (d.b.h.) classes. Changing the flex factor changes the shape of the desired stocking curve. For this study, however, the default values used in the westwide biomass assessment were used.

### **Crowning and Torching Indexes**

Torching index is the wind speed, in miles per hour (mph), at which a surface fire would climb into the crowns of individual trees, and crowning index is the wind speed at which a crown fire would spread from crown to crown. Larger values for both indexes indicate lower fire hazard. In this study, plots with crowning or torching index values below 20 mph were considered suitable candidates for thinning to reduce fire hazard.

The NEXUS 2.0 (Scott and Reinhardt 2001) crown fire hazard analysis software was incorporated into the FTE and used to estimate crowning and torching indexes for all Forest Inventory and Analysis (FIA) plots before and after simulated thinning. The NEXUS program links separate models of surface and crown fire behavior to compute indexes of relative crown fire potential.

Unfortunately, the 2002 RPA data set does not contain information on standing dead and down woody material. This information is necessary to more accurately assess fire hazard. Not having this information results in the underestimation of fire hazard.

Standing dead and down woody material data are currently being collected and will be available in future versions of the FIA database.

### **Harvest Economics**

The harvest economics module was based on the STHARVEST program (Fight *et al.* 2003). The STHARVEST model and software program is a general model that is intended to be used for broad planning applications. It develops estimates of harvesting

cost for six harvesting systems for an average tree size ranging from 1 to 80 or 150 cubic feet, depending on the system selected. Cost estimates are in U.S. dollars per 100 cubic feet or per green ton.

### Geospatial Layers

Attributes from two geospatial layers were added to each 2002 RPA plot record: (1) current fire condition classes and (2) WUI class.

“Condition classes are a function of the degree of departure from historical fire regimes resulting in alterations of key ecosystem components such as species composition, structural stage, stand age, and canopy closure” (Schmidt *et al.* 2002). In the westwide biomass assessment, fire condition class was used exclusively as a measure of fire hazard. In the FTE, torching and crowning indexes derived from FIA data fulfill this role. The ability to report by fire condition class has been retained for comparison purposes.

The wildland-urban interface (WUI) is defined as the area where structures and other human development meet or intermingle with undeveloped wildland. The expansion of the WUI in recent decades has significant implications for wildfire management and impact. The WUI creates an environment in which fire can move readily between structural and vegetation fuels. Its expansion has increased the likelihood that wildfires will threaten structures and people (Radeloff *et al.* 2005).

The FTE gives the analyst the ability to restrict the analysis area to certain WUI classes. The FTE also enables the analyst to view treatment results by WUI class.

### Results

The results come from a single run of the FTE that illustrates a potential thinning alternative for 15 Western States. Only stands with both crowning and torching indexes of less than 20 mph were included (high fire hazard). A silvicultural prescription of thinning until the SDI was reduced to 30 percent of the maximum

was selected, and no flex factor was applied. An additional requirement that the thinning prescription result in a minimum harvest of 300 cubic feet per acre was imposed.

The FTE program generates 7 bar charts and 31 tables of output for each run. A subset of this output is presented for this alternative. In addition to these charts and tables, dynamic maps can be generated depicting biomass, numbers of trees, or growing-stock volume. The mapping units can be set to either counties or Ecological Mapping and Assessment Program hexagons (hexagons approximately 160,000 acres in size). The maps can depict pretreatment condition, post-treatment condition, or the amount of material to be removed by the treatment. Figure 1 is a map of pretreatment growing-stock volume, in cubic feet, per acre of all land.

The thinning prescription would remove a large number of trees. Most trees would come from the smaller diameter classes (fig. 2). Most of the biomass, however, would come from the larger diameter classes (fig. 3).

This silvicultural prescription was not completely effective in increasing the crowning and torching indexes above 20 mph. Only plots that had a crowning and/or torching index of less than 20 mph were considered for treatment in this study. After

Figure 1.—Pretreatment growing-stock volume, in  $ft^3$ , per acre of all land, 2002.

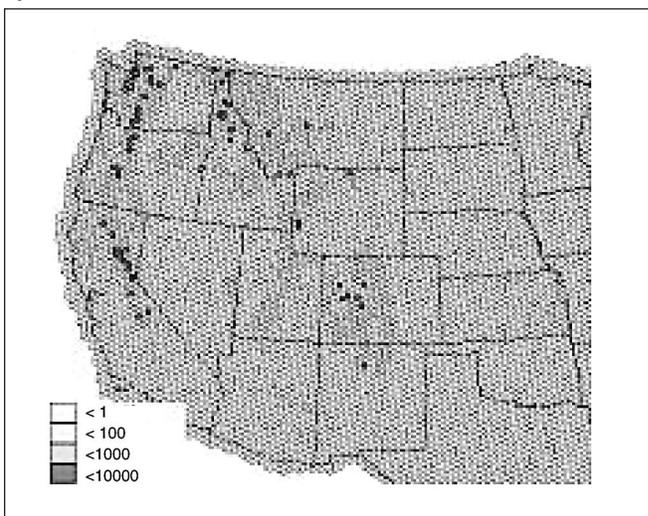


Figure 2.—Live trees per acre by diameter class.

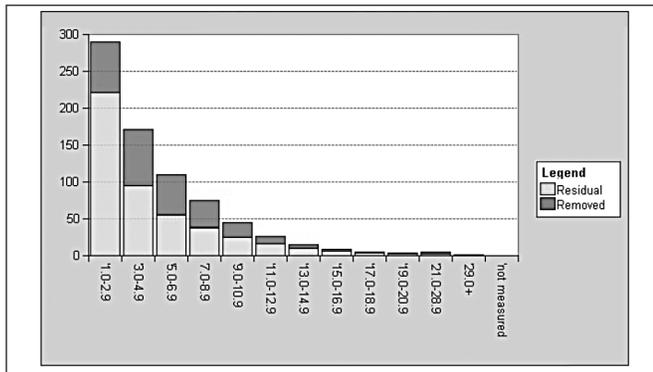


Figure 3.—Live tree dry biomass tons per acre.

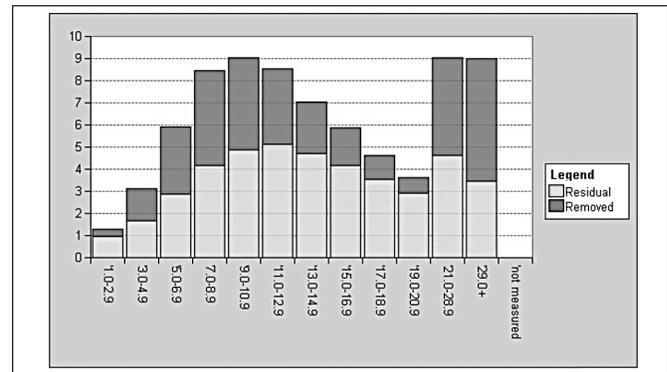
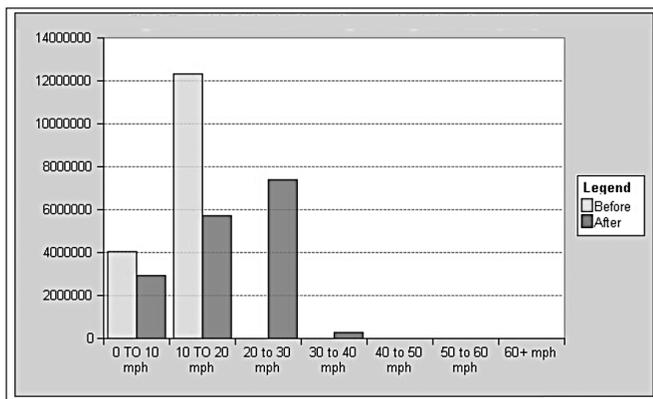


Figure 4.—Treatable timberland area by crowning index class (acres).



treatment, 53 percent of the area represented by these plots still had a crowning index of less than 20 mph (fig. 4), and 51 percent had a torching index of less than 20 mph. Adjustment of the thinning prescription to remove additional biomass is needed, especially in the lower diameter classes.

The FTE generates 31 tables of output. This information can be grouped into two broad categories: information to help calibrate the alternatives and information that can be used in a broad assessment. Table 1 contains output from the FTE that could be used in an assessment. It provides information on the impacts of the alternative by State. Montana had the largest area of treatable timberland in this study with more than 2.6 million acres. California had the largest potential yield with almost 100 million dry tons.

Table 1.—Treatable acres and potential yield by State for alternative thinning treatment.

State	Total treatable acres	Potential yield (dry tons)
Montana	2,648,318	70,929,635
Colorado	2,549,387	65,551,237
California	2,132,695	97,676,889
Idaho	1,892,542	60,361,378
Washington	1,621,094	68,053,090
Oregon	1,371,935	63,667,586
Utah	870,716	23,073,807
Wyoming	847,337	23,797,380
Kansas	751,545	17,186,238
New Mexico	638,171	16,646,198
Nebraska	470,594	10,750,054
North Dakota	193,428	4,528,753
Arizona	181,743	6,922,558
South Dakota	145,438	2,698,311
Nevada	40,904	883,991
Total	16,355,846	532,727,105

Identifying forest areas that have high concentrations of people and property is essential for prioritizing areas to be treated for fuel reduction. Incorporation of the WUI layer into the FTE program enables planners, policymakers, and land managers to identify areas that have a high fire risk and pose a significant threat to life and property. Table 2 provides information on the impacts of alternatives by WUI class. Resources should be directed to those States with large areas of treatable acres in the interface and intermix WUI classes.

Table 2.—Treatable acres and potential yield by WUI class for thinning treatment.

WUI class	Acres	Potential yield (dry tons)
Interface	48,217	1,760,636
Intermix	8,448,689	255,609,982
Uninhabited	6,980,132	253,524,483
Wildland	685,536	16,317,959
NoVeg and others	878,808	21,832,003
Total	16,355,846	532,727,105

## Conclusions

The inputs to the FTE in this study were similar to those used in the westwide biomass assessment. The two major differences were the substitution of plot crowning and torching indexes for current fire condition class and the constraint that at least 300 cubic feet of growing-stock volume should be removed under the prescription. These two changes resulted in the treatment area being reduced from 28 million acres to 16 million acres. Additional refinement of alternatives should focus on identifying areas in close proximity to populated places.

The 2002 RPA database did not have information on standing dead or down woody material. These inputs, which are important to the crowning and torching indexes, will be available in the future and need to be incorporated in the FTE.

The FTE is a relatively simple model that links FIA data with a silvicultural treatment model, a fire hazard model, a harvest cost model, and geosocial data to provide information for broad strategic assessments. More sophisticated models, such as BioSum or FVS, may be needed for regional or local planning.

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## Linking Fuel Inventories With Atmospheric Data for Assessment of Fire Danger

Christopher W. Woodall<sup>1</sup>, Joseph Charney<sup>2</sup>, Greg Liknes<sup>3</sup>, and Brian Potter<sup>4</sup>

**Abstract.**—Combining forest fuel maps and real-time atmospheric data may enable creation of more dynamic and comprehensive fire danger assessments. The goal of this study was to combine fuel maps, based on data from the Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture Forest Service, with real-time atmospheric data to create a more dynamic index of fire danger. Fuel loadings were estimated for points on a meteorological modeling grid network (4 x 4 km) based on FIA's strategic-scale fuel inventory. In addition, fuel moisture at each grid point was predicted based on atmospheric observations over an 11-day period. A Burnable Fuels Index (BFI), combining both fuel loadings and moisture predictions, was investigated for changes in fire danger over the modeled period of time. The BFI was temporally and spatially variable due to heterogeneous forest fuel conditions and dynamic weather events. Overall, combining fuel-loading estimates with atmospheric data enables the current assessment and 1 to 2-day prediction of fire danger and greater understanding of fire danger across forest ecosystems with varying fuel loadings and weather conditions.

### Fire Danger Assessment

Fire danger is defined in terms of factors affecting fire inception, spread, resistance to control, and subsequent damage (NWCG 1996). Fire danger is usually expressed as an index based on component variables and quantified using fire danger rating or prediction systems such as the U.S. National Fire Danger

Rating System (NFDRS) (Deeming *et al.* 1977) and the Canadian Forest Fire Danger Rating System (Stocks *et al.* 1989). Fire behavior models employ fuel loading and fuel moisture information to predict fire behavior, which, in turn, contributes to the development of fire danger rating systems (Andrews 1986, Finney 1998). Fuel loadings are often static for time scales of hours and days, while fuel moisture is variable across time scales of an hour or less. Fuel loadings and fuel moisture are both spatially variable at small scales (e.g., stand level), but fuel moisture is difficult to measure accurately because of high variability over short time scales. As a result, spatially averaged fuel moisture observations are generally used in fire danger assessments over large areas. To better mesh the collection and integration of fuel loadings and moisture in fire behavior prediction models, NFDRS classifies fuel loadings by fuel-hour classes (Deeming *et al.* 1977). For example, a 1-hr fuel is downed woody material with moisture fluctuations at the time scale of hours and is characterized by diameters of less than 0.25 inches. Fuel hour classes with moisture fluctuations at greater time scales are larger in size. For the fire danger of any forest area to be determined, estimates of its fuel loadings and moisture need to be assessed in real time and incorporated into a fire danger index. Despite extensive work over the past decades to quantify fire behavior and subsequent fire danger, inadequate data and technology has impeded real-time assessments of fire dangers. Modern fuel inventories and recent meteorological advances may provide opportunities to determine and provide 1- to 2-day predictions of fire danger.

### Large-Scale Fuel Inventories

The Forest Inventory and Analysis program (FIA) of the U.S. Department of Agriculture (USDA) Forest Service conducts a three-phase inventory of forest attributes of the United States

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(Bechtold and Patterson 2005). The FIA sampling design is based on a tessellation of the United States into approximate 6,000-acre hexagons with at least one permanent plot established in each hexagon. In phase 1, the population of interest is stratified, and plots are assigned to strata for purposes of increasing the precision of estimates. In phase 2, tree and site attributes are measured for plots established in the 6,000-acre hexagons. In phase 3, a 1/16<sup>th</sup> subset of phase 2 plots is measured for forest health indicators such as down woody materials. Down woody components observed by the FIA program are coarse woody, fine woody, litter, herb/shrubs, slash, duff, and fuelbed depth. As defined by the FIA program, fine woody debris (FWD) are downed woody materials with transect diameters less than 3.00 inches. FWD are sampled on each FIA subplot along one transect. One- and 10-hr FWD (transect diameters between 0–0.25 and 0.26–1.0 inches, respectively) are sampled along a 6-ft transect, while 100-hr fine woody fuels (1.0–3.0 inches) are sampled along a 10-ft transect. For additional sampling design information, see Woodall and Williams (in press).

The FWD sampled by the FIA program match the fuel classification system (1-, 10-, and 100-hr) of the NFDRS, enabling creation of strategic-scale fuel maps that may be used to assess fire danger (Woodall *et al.* 2004). Because of the relatively

sparse sample intensity of the FIA fuels inventory, inverse distance weighting interpolation techniques are often used to predict fuel loadings between sample plots. After fuel interpolation, non-forested areas are masked out of the fuel maps using classified imagery, such as the National Land Cover Data (Vogelmann *et al.* 2001), as used in this study (fig. 1). Numerous techniques are available for creating large-scale fuel maps ranging from relatively simple interpolation techniques of FIA fuels data, as used in this study, to more sophisticated efforts demonstrated by Rollins *et al.* (2004) and the USDA Forest Service's LAND-FIRE program ([www.landfire.gov](http://www.landfire.gov)).

### Fuel Moisture and Mesoscale Models

Estimates of surface fuels and real-time weather data are necessary to estimate fuel moisture conditions and fire danger. Numerical weather prediction models can produce daily simulations of atmospheric conditions such as temperature, winds, relative humidity, and rainfall for regions ranging in size from continents to counties. One such model, the Penn State University/National Center for Atmospheric Research Mesoscale Model called MM5, simulates the weather conditions for areas of about one-third the size of a continent down to State and county levels (Grell *et al.* 1994). The MM5 can be run daily, using observations collected and processed at the beginning of each day, to produce a sequence of 24-hr simulations of weather conditions across a region.

The Eastern Area Modeling Consortium (EAMC) is a multiagency coalition of researchers, fire managers, air quality managers, and natural resource managers conducting research and developing new products to improve fire-weather and smoke transport predictions in the north-central and Northeastern United States. The EAMC runs the MM5 daily for the north-central and Northeastern United States in support of fire-weather research and applications. One application of this atmospheric data uses the Canadian Fire Weather Index System (CFWI) (Van Wagner 1987) to calculate fuel moisture variations across the model geographic domains based on simulated temperature, relative humidity, and rainfall information. These calculations use the Fine Fuel Moisture Code in the CFWI to generate daily values for fuel moisture that roughly correspond to the expected

Figure 1.—Regional map of fine wood fuels based on inverse distance weighting interpolation of 500 FIA fuel inventory plots and nonforest mask (classified NLCD 1992 imagery) in the upper Great Lakes region.

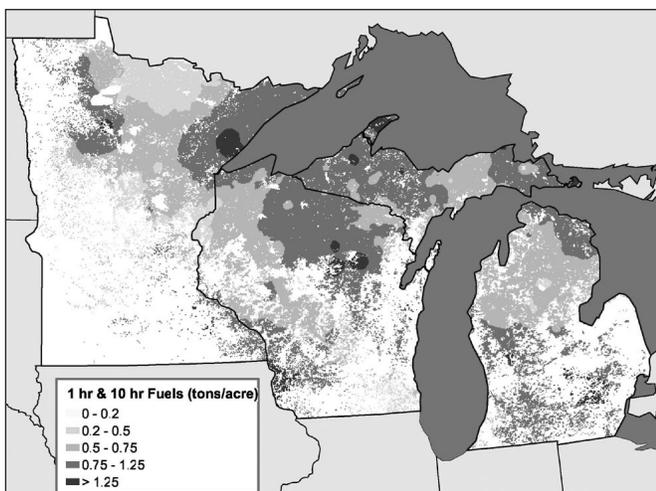
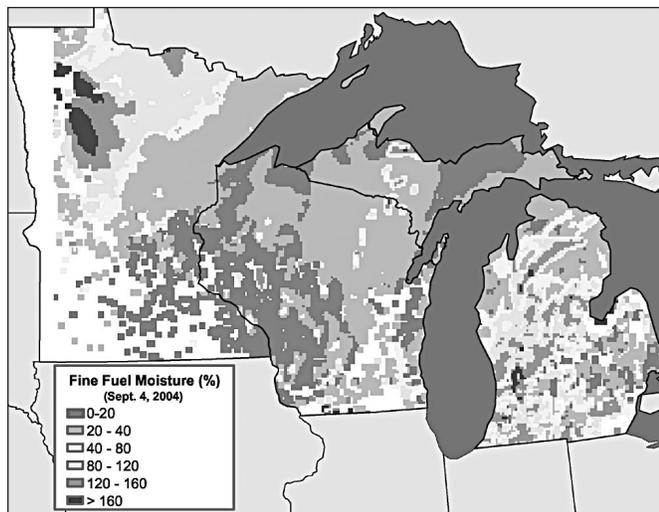


Figure 2.—Fine woody (1- and 10-hr) fuel moisture map for study area, upper Great Lakes, September 4, 2004.



variations in 1- and 10-hr fuels, as defined by the NFDRS. Fine-fuel moisture estimates from the EAMC’s mesoscale models may be produced for any forest ecosystems on any given day (fig. 2).

### Merging Fuels and Moisture Estimates

To create a more dynamic regional view of fire danger, we sought to combine maps of regional fuel loadings (interpolated FIA fuel map, fig. 1) and fuel moisture (EAMC mesoscale models, (fig. 2) for the upper Great Lakes. First, fuel loadings (1- and 10-hr FWD) were obtained from FIA’s interpolated fuel maps for a 4 x 4-km grid (13,136 forested grid points) across the upper Great Lakes used by the EAMC’s mesoscale model. Second, to address the effects of fuel loading and fuel moisture, the two estimates were combined into a single meaningful quantity that is applicable to operational fire activities. As a rule of thumb, fire danger can be considered to increase when fuel moistures fall below 30 percent, which is the fiber saturation point in dead fuels (Zhou *et al.* 2003). To accentuate the effects of this threshold, we developed the Burnable Fuels Index (BFI), formulated as follows:

$$BFI = (0.3 - m) FL \quad (1)$$

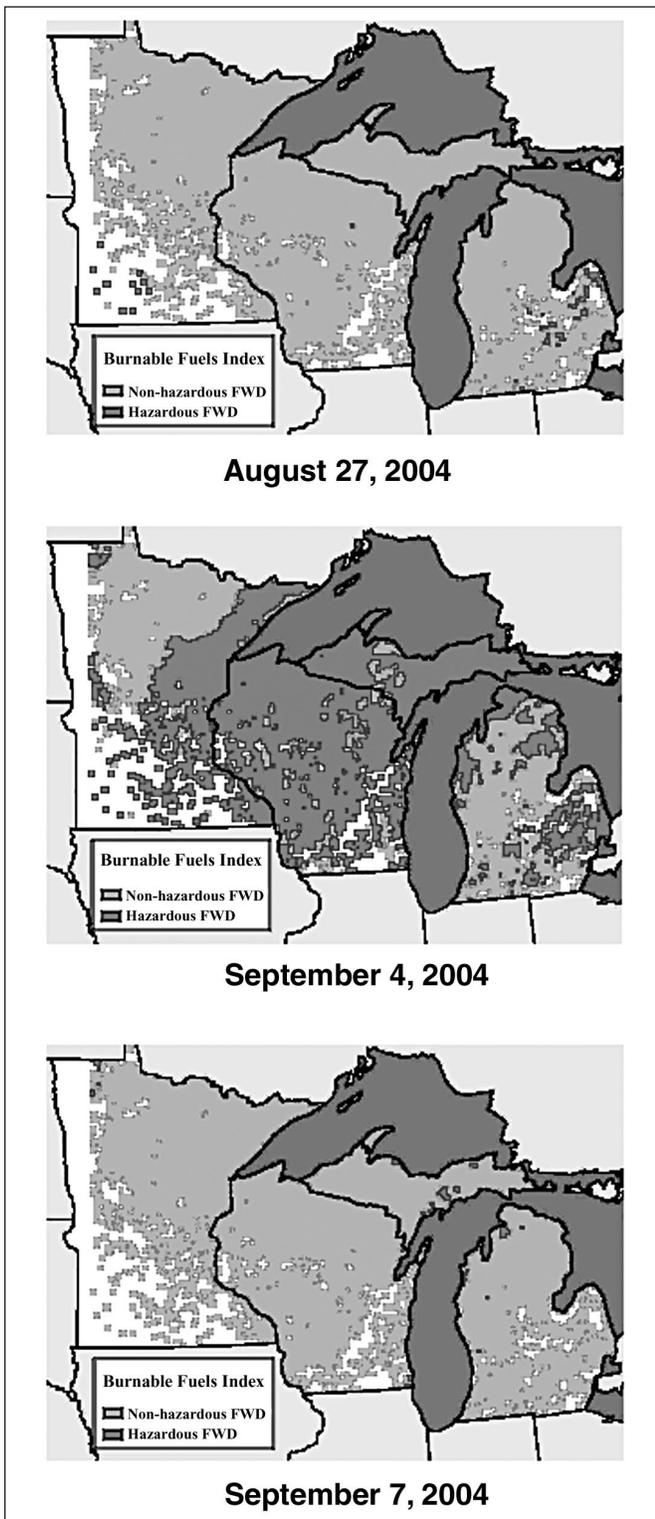
where  $m$  is the simulated fuel moisture between 0 and 1 (0 and 100 percent), and  $FL$  is the fuel loading in tons/acre. BFI is negative when fuel moistures exceed 30 percent. Conversely, BFI will increase as fuel moistures decrease below 30 percent and as fuel loadings increase. This quantity offers no insight into the probability of ignition and does not account for long-term precipitation effects on the heavier fuels. BFI is most useful, however, when used in conjunction with observations of moisture variations in the heavier fuels and local knowledge of fuel and forest conditions and at strategic scales may aid comprehension of how fire danger varies by day and user-defined areas.

### Initial Results and Future Possibilities

In the upper Great Lakes region of the United States, fire danger may vary daily over a “fire season.” Results from this study indicated dangers from 1- and 10-hr fuels varied from almost no danger (August 27 and September 7, 2004) to moderate danger (September 4, 2004) over a span of a few days (fig. 3). Areas with positive BFI (hazardous FWD) were typically constrained to areas that had “dried out” following the precipitation of recent weather fronts and before the arrival of a new weather front (fig. 3). Linking real-time estimates of fuel moisture with static fuel maps may allow refinement of fire behavior predictions and subsequent wildland firefighting efforts.

Because this study served as an initial examination of the techniques and outputs of merging strategic-scale fuel maps with real-time weather data, numerous refinements are needed to enable widespread application. First, BFI needs to better reflect fuel and fuel moisture relationships that are likely not multiplicative. Second, although inverse distance weighted interpolation of FIA phase 3 plots is an efficient and simple methodology for creating regional fuel maps, other techniques and data sources exist to complement and further improve regional fuel data layers. Lastly, data dissemination techniques that facilitate real-time Web updates of BFI maps are necessary to incorporate them into fire season activities. Overall, the results of this study indicate opportunities exist to refine understanding of the dynamic nature of forest fire dangers.

Figure 3.—Burnable fuel index before (August 27), during (September 4), and after (September 7) a major weather event over a 3-day time-step during the summer of 2004, upper Great Lakes.



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## Urban Forest Health Monitoring in the United States

**David J. Nowak, Daniel Twardus, Robert Hoehn, Manfred Mielke, Bill Smith, Jeffrey T. Walton, Daniel E. Crane, Anne Cumming, and Jack C. Stevens<sup>1</sup>**

**Abstract.**—To better understand the urban forest resource and its numerous values, the U.S. Department of Agriculture Forest Service has initiated a pilot program to sample the urban tree population in Indiana, Wisconsin, and New Jersey and statewide urban street tree populations in Maryland, Wisconsin, and Massachusetts. Results from the pilot study in Indiana revealed that about 92.7 million urban trees exist with a structural value of \$55.7 billion. These trees removed about 6,600 metric tons of air pollution in 2000 (\$35.4 million value) and store about 8.4 million metric tons of carbon (\$170.2 million value).

People are having an ever-increasing impact on local, regional, and global environments, particularly in and around urban areas (cities, towns, villages). Urban forests (trees in urban areas) can mitigate certain detrimental human impacts and improve environmental quality and human health. Urban forests help provide clean air and water, reduce building energy use, store carbon, protect against ultraviolet radiation, and cool air temperatures. They also provide forest-based products, recreation opportunities, habitat for wildlife, aesthetic enjoyment, and enhance the social and psychological well-being of millions of Americans. This valuable national resource will continue to increase in extent and importance in the years ahead, yet faces numerous pressures such as insects, diseases, storms, and pollution that affect forest health and related benefits.

In 1997, a National Research Council report, “Forest Lands in Perspective,” recognized that urban and community non-Federal forests are the fastest growing forests in the United States. It recommended strengthening Federal monitoring of the health of these forests. In 1998, USDA Forest Service Chief Michael Dombeck developed a Natural Resource Agenda that emphasized sustainable development of communities, and Deputy Chief Phil Janik released an action strategy for State and Private Forestry that would increase forest health monitoring in urban areas. In 1999, USDA Secretary Dan Glickman noted, “We still have plenty of work to do to make Americans take notice of the dwindling natural resource base in their cities.”

In a survey of forestry professionals regarding the health needs of urban forests, less than 25 percent of the respondents ranked the overall health of the urban forests in their State as good to excellent; 99 percent indicated that preserving the health of community forests should be an integral part of urban and community forest programs; and more than 90 percent identified long-term tree care and maintenance programs as critical to preserving the health and sustainability of urban forests in the Northeast (Pokorny 1998).

Although urban forests affect the vast majority of Americans, little is known about them, how they are changing, or the factors that might lead to changes in the structure and health of this valuable resource. Knowing how the urban forest is changing can aid in developing more effective policies for protecting, sustaining, and otherwise enhancing the health of and benefits derived from this resource for future generations. To learn more about urban forests and aid in their management and planning, pilot studies were conducted to evaluate the implementation of

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a national Urban Forest Health Monitoring (UFHM) program. The purpose of this program is to acquire information about the urban forest while concurrently establishing a nationwide system of pest detection and health monitoring in urban forests (Nowak *et al.* 2001). The UFHM program is a cooperative effort among the USDA Forest Service's Forest Health Monitoring program, Urban and Community Forestry, Forest Inventory and Analysis (FIA), Northeastern Research Station, and State agencies.

As part of this program, two field sampling protocols were developed. The first is designed to assess the entire urban forest resource (Urban Forest Inventory); the second focuses on the street tree resource (Statewide Urban Street Tree Monitoring). This article reviews the status of the UFHM program and reports results from the first Urban Forest Inventory pilot study in Indiana and the Statewide Urban Street Tree Monitoring pilot studies in Maryland and Massachusetts.

## Urban Forest Inventory

Urban Forest Inventory uses the FIA sampling grid that was designed to collect information about forests nationwide. FIA is responsible for periodic assessments of the Nation's forest resources as well as statewide inventories. Currently data are collected only on "forested" plots, defined as areas at least 1 acre in size and at least 120 feet wide, at least 10-percent stocked, and not intended for uses other than forest. Thus, field data are not collected on "nonforest" plots, such as urban areas, even though such plots might contain many trees. As most urban areas are classified as nonforest, data on urban vegetation are often not collected as part of the national FIA program. The urban forest inventory phase of the UFHM program is designed to collect data on FIA plots in urban areas to fill this critical "data gap."

The FIA grid was used to sample plots in urban areas (1 plot for every 6,000 acres). Boundaries of urban areas are based on data from the U.S. Census Bureau and overlaid on the FIA grid. Plots within the urban boundaries classified as nonforest are included in the UFHM inventory. Urban nonforest plots are sampled during the growing season to provide an extended suite

of ecological data that includes a full vegetation inventory and evaluation of tree damage and crown conditions, and information on variables needed for analyses using the Urban Forest Effects model (e.g., percent crown missing, distance from building) (Nowak and Crane 2000). For a complete urban analysis, data from existing FIA forest plots in urban areas were combined with the new nonforest UFHM plots. Riemann (2003) found that the cost of measuring urban nonforest plots is about one-third of that for a forested FIA plot.

Pilot implementation of the inventory in Indiana, conducted in 2001 and 2002 by the Indiana Department of Natural Resources, was designed to extend the ongoing FIA statewide inventory into urban areas. This extension resulted in 32 sample locations within urban boundaries (six locations met the FIA definition of forested and were excluded as data already existed at these locations as part of the national FIA program). Because the Indiana inventory was designed to be completed (all plots) over a 5-year period, only one-fifth of the total number of urban sample locations were collected during the first year.

A second pilot study in Wisconsin in 2002 was conducted in cooperation with the Wisconsin Department of Natural Resources. In all, 119 urban nonforest plots were sampled (plus 28 previously measured FIA forest plots in urban areas). All urban nonforest plots in Wisconsin (1 plot every 6,000 acres) were established and measured in the first year. After the first year of complete data collection, the inventory was designed to monitor one-fifth of the plots each year so that all plots are updated in 5 years. A third inventory pilot was initiated in New Jersey in 2003.

Urban forest inventory plots consist of four 24-foot, fixed-radius subplots spaced 120 feet apart. This particular plot layout, although useful in forested situations, has proven more difficult in urban settings. The distance between subplots often results in numerous contacts with property owners to establish a plot. In Wisconsin, an average of five owner contacts was made per plot, and 12 owner contacts were recorded for a single plot. Training of field crews included extensive manual review and field demonstrations of plot layout and tree measurements. Plot remeasurements and checks were conducted to maintain data quality.

The FIA National Core Field Guide was modified for urban nonforest data collection to include urban land-use codes; plantable space; and subplot tree, shrub, and ground cover information. An extended tree species code list has been incorporated, and all trees 1 inch and larger in diameter on urban nonforest plots are measured. An urban FIA field guide can be accessed at <http://www.fs.fed.us/ne/syracuse/Tools/tools.htm>.

### Indiana Urban Forest Inventory

Within the urban areas of Indiana are an estimated 92.7 million trees (standard error [SE] = 32.8 million). Of these trees, about 49.1 million (SE = 26.8 million) are in forests in urban areas; the remaining 43.6 million (SE = 19.1 million) are in other urban uses (e.g., residential, vacant, and commercial/industrial). The most common tree species were sassafras (15.1 percent), silver maple (14.6 percent), and eastern cottonwood (10.9 percent). In forest areas, sassafras (28.6 percent), northern red oak (15.8 percent), and white oak (11.0 percent) dominated; on other urban lands, silver maple (24.5 percent), eastern cottonwood (18.2 percent), and Siberian elm (9.5 percent) were the most common. Most trees in the total urban forest are small (less than 3 inches in diameter) (fig. 1).

Silver maple is the dominant species in basal area, which is related to tree size and functional value. Trees that are relatively small (percent basal area much less than percent total population) include sassafras, eastern cottonwood, American basswood, and

boxelder (fig. 2). Species that are not native to Indiana make up 7 to 14 percent of the urban forest stands and 18 to 20 percent of the remaining nonforest urban lands.

Trees cover about 20 percent of Indiana's urban area versus about 8 percent for shrubs. Other cover types include herbaceous cover (e.g., grass and gardens) (46 percent); impervious surfaces including buildings (28 percent); duff, mulch, and bare soil (24 percent); and water (2 percent). Ground cover in forested stands is dominated by duff/mulch, while other urban lands are dominated by herbaceous ground cover.

Urban forests have a structural value based on the tree resource itself (e.g., the cost of replacing the tree with a similar one), and annually produce positive or negative functional values based on functions performed by the tree. The structural or compensatory value (Nowak *et al.* 2002) of Indiana's urban forest is nearly \$56 billion.

Urban trees in Indiana remove an estimated 6,600 metric tons of pollution per year, with an associated value of about \$35.4 million (based on estimated national median external costs associated with air pollution). Pollution removal was greatest for ozone, followed by particulate matter less than 10 microns, sulfur dioxide, nitrogen dioxide, and carbon monoxide (fig. 3).

Figure 1.—Diameter distribution of trees in Indiana's urban forest.

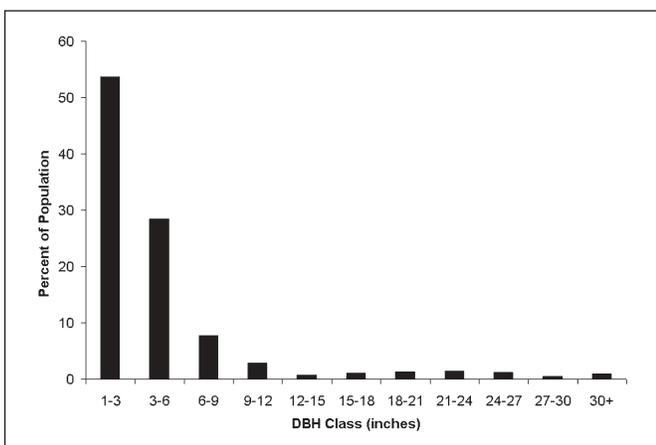


Figure 2.—Percentage of population and percentage of basal area for the 12 most common tree species in Indiana's urban forest.

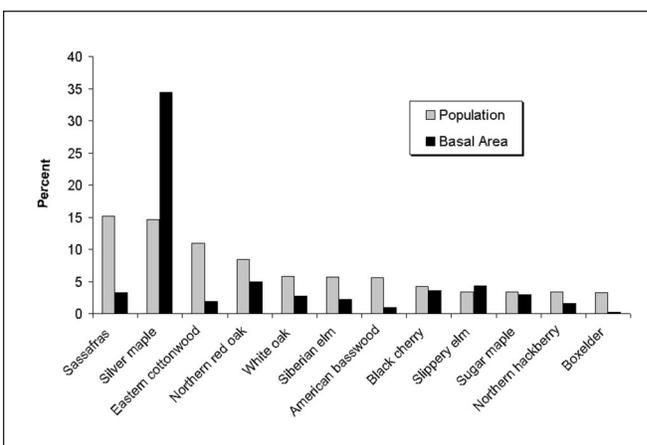
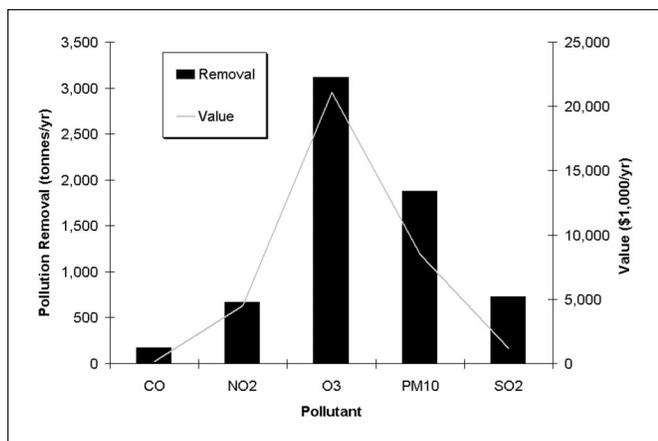


Figure 3.—Estimated pollution removal (2000) by Indiana’s urban forest. Removal value estimated using median externality values in the United States for each pollutant: nitrogen dioxide ( $NO_2$ ) =  $\$6,750 \text{ t}^{-1}$ , particulate matter < 10 microns ( $PM_{10}$ ) =  $\$4,500 \text{ t}^{-1}$ , sulfur dioxide ( $SO_2$ ) =  $\$1,650 \text{ t}^{-1}$ , carbon dioxide ( $CO$ ) =  $\$950 \text{ t}^{-1}$  (Murray et al. 1994). Externality values for  $O_3$  were set to equal those for  $NO_2$ .



Urban trees in Indiana store an estimated 8.4 million metric tons of carbon (\$170.2 million value). Of the species sampled, silver maple stores the most carbon (about 32 percent of all carbon stored). Urban trees sequester an estimated 280,000 metric tons of carbon annually (\$5.7 million).

Urban trees in Indiana save homeowners an estimated \$14.7 million annually by reducing electricity energy consumption. However, tree shade from branches increases costs by \$20.8 million annually due to increased fuel usage to heat buildings in the winter. The net effect of the current structure is an annual cost of \$6.1 million. Although costs go up, Indiana’s urban forest reduces carbon emissions from power plants by nearly 23,600 metric tons. This disparity is due to the difference between cost and carbon production involving energy use in winter and summer. Because tree location around buildings and tree size are key determinants of energy effects, the small sample size combined with relatively few trees in energy effect positions means the results of this analysis are highly uncertain.

Exotic pests also can have a significant influence on Indiana’s urban forest. The Asian longhorned beetle (ALB) bores into and kills a wide range of hardwood species (USDA Forest

Service 2004a). The risk from ALB to Indiana’s urban forest is a loss of \$30.3 billion in structural value (57.8 percent of the population). The gypsy moth feeds on a variety of tree species and can cause widespread defoliation and mortality if outbreak conditions last for several years (USDA Forest Service 2004b). The risk from this pest in Indiana is a loss of \$9.0 billion in structural value (22.7 percent of population). The risk from the emerald ash borer, which has killed thousands of ash trees in Michigan, Ohio and Indiana (USDA Forest Service 2004c), is \$2.9 billion in structural value (1.9 percent of population).

The overall pilot test was based on 32 plots, which is a relatively small sample. Increased sample size with future measurements will increase confidence in the results.

### Statewide Urban Street Tree Monitoring

Statewide Urban Street Tree Monitoring assesses street trees using plots established randomly in the public right-of-way in urban areas. Although they account for a small portion of the urban forest (approximately 5 to 10 percent), street trees are the resource that municipal foresters are responsible for and often are the most visible component of the urban forest. A monitoring system provides data on the nature and condition of the street tree population and can be used to detect new or exotic insects or pathogens. Like urban forest inventory plots, street tree plots are updated continually to provide data on changes in tree populations.

The statewide sample consists of 300 street tree plots. In the first year, all 300 plots are installed; this becomes the baseline sample. In subsequent years, a subsample of plots is revisited to allow for assessments of change. A State may choose to intensify the baseline sample. This intensification was done in Wisconsin in 2002 when 900 plots were installed by the Wisconsin Department of Natural Resources. The Massachusetts Division of Forests and Parks (2002) and Maryland Department of Agriculture (2001) each installed 300 baseline plots. In 2002, in Maryland, plots were revisited using a rotating panel design to obtain an estimate of year-to-year change in condition. A panel consists of one-fifth of the 300 baseline plots along with a remeasurement of one-third of the previous year’s plots (20 overlap plots) for a total of 80 plots per year.

Each plot consists of four subplots, two on each side of the roadway. Plots were installed within the public right-of-way, so property owner contacts were not an issue. Each subplot is 181.5 feet long and 10 feet wide (area equals the area of an urban forest inventory subplot). Instructions were provided for cul-de-sacs, dead-end roadways, and roads with median strips. Although not set permanently with monument markers, plot locations are identified by distance and azimuth to landmarks. Divided highways, private communities, interstate access ramps, and military installations were excluded as sample locations. Plot locations were provided to State personnel along with replacement locations if the original plots could not be accessed (e.g., plots with dangerous access or located in private or gated communities).

A street tree manual includes information on plot establishment procedures and data collection. All trees 1 inch and larger in diameter are tallied. Data are collected on tree diameter and height, crown condition, and damage. Ground-cover types on the plot are estimated, and information on sidewalk and utility conflicts is recorded. Training was conducted for all field crews and included a review of the field manual and procedures for in-field plot establishment.

### Street Tree Monitoring in Maryland and Massachusetts

An estimated 643,958 trees exist along Maryland's 14,139 miles of urban roadway (about 46 trees per mile). The 20,384 miles of urban roads in Massachusetts are lined with an estimated

1,184,776 trees (58 trees per mile). In Maryland, the street tree population comprises 67 different species, none making up more than 13 percent of the total population (table 1). Species diversity at the genus level shows 32 different genera, with more than 70 percent of the trees among only five genera (*Acer*, *Pyrus*, *Quercus*, *Prunus*, and *Platanus*). In Massachusetts, Norway maple clearly dominates, accounting for nearly 35 percent of the 66 species encountered (table 2). Massachusetts street trees are represented by 29 different genera, with more than half of all trees either *Acer* or *Quercus*.

The street population in both States is dominated by maples; nearly half of the trees in Massachusetts and 40 percent of the trees in Maryland are Norway, sugar, red, silver, or other maples. This distribution has implications for insect or disease infestations that could cause significant losses in street trees. An example is the recently introduced ALB, which attacks and kills at least six species of maple. Other potentially significant pests or diseases are the gypsy moth, which could have a significant impact on oaks, the emerald ash borer, and sudden oak death.

Available planting space was determined by factoring an accepted planting space (50 feet) between trees, knowing the proportion of roadways that lack street trees, and considering trees whose crowns overlap the public right-of-way and essentially function as street trees. In Maryland, an estimated 23 plantable spaces exist per mile of urban roadway, and 20 such spaces exist per mile in Massachusetts. Planting potential spaces would nearly double the number of street trees in Maryland but increase

Table 1.—Ten most frequent species found on Maryland's urban roadways.

Species	Percent of total	Mean diameter at breast height (d.b.h.) (inches)
Callery pear	13	9
Red maple	11	13
Maple spp.	10	10
Norway maple	6	11
Silver maple	5	13
Cherry/Plum	3	6
Oak spp.	3	16
Crabapple	3	10
Honeylocust	3	12
Sweetgum	2	8

Table 2.—Ten most frequent species found on Massachusetts' urban roadways.

Species	Percent of total	Mean d.b.h. (inches)
Norway maple	34	15
Red maple	9	12
Northern red oak	8	16
Callery pear	4	6
Pitch pine	4	8
White ash	3	19
Black oak	3	9
White oak	3	15
Sugar maple	3	18
Silver maple	3	25

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street trees only about 30 percent in Massachusetts. However, this estimate of potential planting space includes hardscape such as driveways, sidewalks, and other impervious surfaces that could limit tree planting.

Distribution of tree size as reflected by diameter class indicates that street tree populations in Maryland are relatively well distributed; the largest proportion of trees is in the 5- to 15-inch diameter classes. In Massachusetts, larger trees (15 inches and larger in diameter) account for about half of the total, indicating a somewhat older or maturing street tree population. Large street trees are often aesthetically pleasing, but frequently require additional management (e.g., pruning due to interference with sidewalks or overhead wires, or for public safety). Compared to street trees in Maryland, those in Massachusetts had a higher incidence of conflicts involving sidewalks (28 versus 18 percent) and overhead wires (25 versus 18 percent). In Maryland, 64 percent of the trees did not meet the minimum threshold for recording damage compared to 71 percent in Massachusetts. In Maryland, the most common damage recorded was open wounds (16 percent of damage recorded); conks and signs of advanced decay were the most common in Massachusetts (17 percent). Street tree monitoring, particularly in the long term, can provide useful information for sustaining populations, maximizing benefits, and minimizing liability.

## Conclusion

National monitoring of urban forests can provide critical information for improving urban forest health, management, and benefits derived from this valuable resource. Although the information obtained from UFHM plots can be used immediately in management and planning, increased value will be derived after the plots have been remeasured. Long-term tree and forest monitoring in urban areas provides essential information on rates of change as well as a means for detecting and monitoring the spread and range of numerous tree health-related factors (e.g., spread and damage associated with the introduction of exotic pests). Knowing how the urban forest is changing can aid in developing more effective policies for protecting, sustaining, and otherwise enhancing our urban forests for future generations.

## Acknowledgments

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## Regional Monitoring of Nonnative Plant Invasions With the Forest Inventory and Analysis Program

Victor A. Rudis, Andrew Gray, William McWilliams, Renee O'Brien, Cassandra Olson, Sonja Oswalt, and Beth Schulz<sup>1</sup>

**Abstract.**—Monitoring nonnative plant invasions by the Forest Inventory and Analysis Program includes (1) assembly of regional lists of nonnative invasive plant species in forest land, (2) observations at systematic intervals equivalent to a 5-km grid with traditional forest resource measurements, and (3) growing-season observations of all vascular introduced and native plant species at 1/16<sup>th</sup> of those locations (a 22-km grid) with additional forest health measurements. Strengths and limitations of this collective effort are discussed. This report provides lists of species to be monitored, preliminary results that rank infestation probability and severity in southern United States forest land, and highlights from studies of earlier surveys in selected States.

### Introduction

To be effective, management of nonnative plant invasions in forest land requires a strategy that includes regional monitoring to determine the presence and extent of such invasions and the effects of local management activities on pest populations. Such monitoring will make it possible to prioritize management efforts at appropriate spatial scales. Many view plant invasions mainly as a problem affecting agricultural and urban land, but such invasions significantly affect forest land. Invasive plants considered problems are the ones that damage forest resources and transform ecological processes. For example, kudzu (*Pueraria montana*) suppresses tree regeneration and the wood volume growth of established trees by reducing the amount of

light into the forest. Other impacts include modification of habitat for native wildlife, replacement of native forest species, alteration of soil properties, reduction in species diversity, and rapid biomass accumulation that increases the risk of wildfire.

The U.S. Department of Agriculture (USDA) Forest Service's Forest Inventory and Analysis (FIA) program conducts a national forest resource survey that provides a means of studying the problem of plant invasions in forest land. FIA conducts a systematic, sample-based inventory over a large area to provide baseline estimates of representative conditions with a stated range of confidence. These estimates constitute strategic information to guide decisions about the efficient regional allocation of conservation, management, procurement, and production activities.

We report on progress in using FIA surveys for the conterminous United States, share highlights of preliminary findings in addressing the problem of plant invasions, and discuss weaknesses and opportunities for the future. Examples show that FIA survey data can (1) supplement existing knowledge of distributions of nonnative and potentially invasive plant species, (2) provide a sound basis for allocation of increased prevention efforts, (3) be used to identify and map large invasions, or regional hot spots, on forest land, (4) explore plausible correlated relationships among associated attributes, and (5) facilitate calibration of satellite imagery and obtain finer-scaled, mapped estimates of canopy-dominant invasive species.

### Background

Several terms used in this discussion must be defined. *Forest land* is land at least 37 m wide; 0.4-ha in size; covered, or formerly

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covered, by trees; capable of tree-growth; and not developed for nonforest uses. *Timberland* is forest land excluding areas restricted from timber production, such as wilderness, and forest land too wet or too dry to support commercial wood production. A *nonnative* plant species is one that is alien or exotic to the ecosystem under consideration.

In this report, an *invasive species* is a nonnative plant species whose introduction causes or is likely to cause economic or environmental harm. Infested land is land represented by a sampled area in which an invasive plant species is present. Each sampled location represents a portion of the study region. If infested, that portion is the *area of infestation*. The *severity* of the infestation is the portion of the sample covered by the species, and calculated as *total cover* (area of infestation multiplied by the proportion of severity).

The USDA Forest Service has a national strategy for addressing invasive species management (Ries *et al.* 2004), but adaptation of the FIA forest land monitoring effort in the conterminous

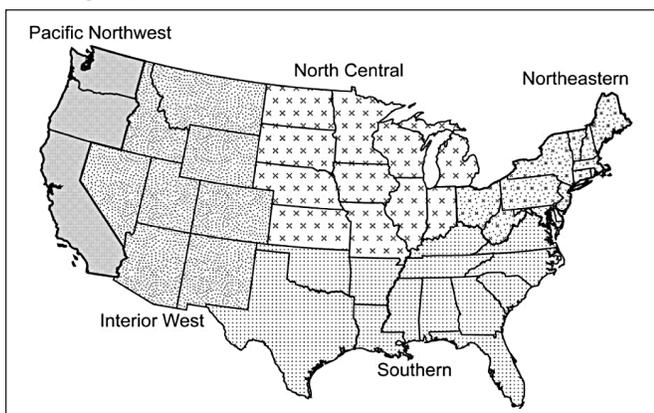
United States has, thus far, been driven primarily by interested parties in FIA's five research work unit regions (fig. 1).

## Methods

Collectively, the efforts of FIA work unit regions to monitor plant invasions may be viewed as a three-tiered task. The first tier is the assembly of a target list of plant species deemed potential problems in one or more FIA regions or States. The second is a survey by Federal and state forest resource survey crews with added training to identify the listed species or taxa from samples of plots on a 5-km grid (a P2 grid) and located on forest land (USDA Forest Service 2001). A third is documentation of the occurrence of introduced species, estimation of their cover, and approximation of the ratio of introduced plant species to all vascular plant species. This third task involves growing-season observations by botanists on a subset of P2 plots, typically 1/16<sup>th</sup> of P2 sample plots and located at 22-km intervals (on a P3 grid), along with other attribute observations (Burkman 2005). The P3 observations include a census of all vascular plant species on three, 1-square-meter areas within each subplot, and cover estimates by species for the subplot (Schulz 2003).

FIA forest resource surveys today operate on a random, systematic sampling grid, with each panel representing a subset of samples from all portions of the grid. Field crews complete a panel without major revisions to a sample protocol, and generally complete a panel in a single year. Thus, the sample design and operational logistics permit observations and analyses with the completion of a panel in a given state. Samples are located at random in a grid cell, which permits calculation of confidence intervals for area estimates by the random sampling formula (O'Brien *et al.* 2003). At each forest land sample location, inventory crews estimate cover by target species on four equidistant 7.3-m radius subplots in a 0.6-ha plot sample area (Burkman 2005). The area of the four subplots, 0.067 ha, is fixed, and crews record observations only on forest land. Forest land may be characterized for a single sample location as those associated with the *forest interior*—none of the subplots are positioned on nonforest land and those associated with *forest edge*—a portion of the subplots is positioned on nonforest land.

Figure 1.—FIA survey regions of the conterminous United States: Interior West (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming), Northeastern (Connecticut, Delaware, Maine, Massachusetts, Maryland, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, West Virginia), North Central (Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, Wisconsin), Pacific Northwest (California, Oregon, Washington), and Southern (south central States—Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, Tennessee, Texas—and southeastern States—Florida, Georgia, North Carolina, South Carolina, and Virginia).



### Target Lists and Measurement Protocols

Each FIA region confers with State agencies and staff from the USDA Forest Service and assembles a target list of potential problem species to be inventoried on forest land. Published lists of problem species are consulted; these may include those on the Federal Noxious Weed List (Federal Register 2004), State noxious weed lists, and national forest district or region lists of species of concern, species discouraged for restoration, or prohibited from introduction (Southeast Exotic Pest Plant Council 2001; USDA Forest Service, Pacific Northwest Region 2004; USDA Forest Service, Pacific Southwest Region 2001). The USDA Natural Resources Conservation Service (NRCS) PLANTS Database (USDA NRCS 2004) also is referenced to confirm that the species selected are documented as occurring in the region.

A regional consensus on what nonnative species are potential problems sufficient to warrant monitoring is not always possible. Some State and other Federal agencies collect FIA field observations themselves and have an influence on the selection of species. In the Eastern United States, each FIA region's staffs typically shorten the list to those that are easily identifiable and known to occur in forest land. FIA regions in the West place formally designated noxious species on their target lists on request by interested groups, such as State forestry agencies and national forest districts.

FIA assigns a unique national code to each nonnative and potentially invasive tree species. By consensus, FIA regions designate several of these as "core-required" (USDA Forest Service 2004). Crews that encounter core-required tree species must uniquely identify the species in the national FIA Database and record its stem attributes for volume, growth, and mortality estimation. Mimosa (*Albizia julibrissin*), a nonnative and reportedly invasive tree species, is an example of a recent addition.

If no consensus exists among FIA regions, the tree species is "core-optional." Each FIA region may identify these uniquely, record other attributes, or ignore the species altogether. Examples include saltcedar (*Tamarix* spp.), which may be of variable form under Western United States moisture regimes, and camphortree (*Cinnamomum camphora*), which typically is a tree only in subtropical and tropical climates. FIA records the cover of saltcedar without stem attributes primarily in the Interior West. FIA records camphortree and its stem attributes in Florida, but ignores this species in other States.

For species designated as nontree species, crews record observations by subplot, but the species (see the appendix) and procedures vary by FIA region (table 1). Identification of nontree species is established by consensus primarily in, rather than among, FIA regions. Procedures for estimating cover are often more compatible with existing or historical protocols for

Table 1.—Protocol for inventories of invasive plant species by FIA region.

Attribute	Western regions		Eastern regions		
	Interior West	Pacific Northwest	North Central	Northeastern	Southern
States implemented	All	All	All	Pennsylvania only	All currently surveyed
Noxious species selected for inventory	All listed by State	National forests and likely on forest land	Regionwide and likely on forest land	By State and likely on forest land	Regionwide and for Florida, likely on forest land
Cover category estimates	Presence (noxious), 1% above 5% (invasive)	≥ 1% (noxious), 1% above 3% (invasive)	< 1, 1–5, 6–10, 11–25, 26–50, 51–75, 76–100%	10% classes	< 1, 1–10, 11–50, 51–90, 91–100
Measurement tolerance	1–5, 6–10, 11–20, 21–40, 41–60, 61–80, 81–100%	1–5, 6–10, 11–20, 21–40, 41–60, 61–80, 81–100%	No error 80% of time	No error 85–90% of time	No error 90% of time

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collection of vegetation data. As demand for national information grows, collaborative standardization for nontree species likely will follow.

### Status of P2 Efforts

The narrative below summarizes the status of FIA's P2 efforts as of September 2004:

- The Northeastern FIA Region conducts a year-round survey. Crews inventory invasive nontree invasive species only during the growing season and only in Pennsylvania. About 300 randomly selected P2 samples are surveyed as part of a special study of tree regeneration. Crews estimate percent cover for 10 taxa and estimate presence or absence for a total of 33 taxa.
- The North Central FIA Region conducts a year-round survey. Crews estimate percent cover for 25 invasive nontree taxa. A 2003 pilot study conducted in Wisconsin during both the growing and dormant seasons indicated that crews could readily identify these species in leaf-off condition. For field identification, crews are using local guides as well as an invasive plant species manual designed to distinguish between similar species (Huebner *et al.* 2004). Informal testing suggested that species identification was consistent across seasons. Assignment of species to categories of growing-season cover is assumed to be consistent from season to season, but this assumption has not been tested.
- The Interior West FIA Region sometimes conducts surveys year-round, but never when snow is on the ground. The understory vegetation survey estimates cover by four life forms and up to four of the most abundant species, including some invasive taxa, with 5 percent or more cover per forested subplot. Crews also record presence of State-listed noxious species, with lists varying in species composition and number between 18 (Idaho) and 71 (Colorado). The ecosystems are diverse, consensus is limited, and observations insufficient at this time to establish a more consistent noxious species list. Identification and assignment of species to categories of growing-season cover are assumed to be consistent from season to season, but this assumption has not been tested.
- The conterminous Pacific Northwest FIA Region conducts surveys primarily during months with no snowfall. Crews record cover for abundant ( $\geq 3$  percent cover), easily identifiable taxa. These include about 20 invasive nontree taxa. For national forests in California, crews document presence to 1 percent for each of 11 species deemed noxious. Identification and assignment of species to categories of growing-season cover are assumed to be consistent from season to season, but this assumption has not been tested.
- The Southern FIA Region conducts a year-round survey. Invasive nontree surveys have not yet been initiated in Mississippi, Oklahoma, or west Texas. Crews use a four-season invasive species manual (Miller 2003) for field identification and tally up to four of the most abundant species per forested subplot. Crews estimate percent cover in classes for 33 taxa, plus some 20 species unique to Florida (USDA Forest Service 2001, 2003). Identification and assignment of species to categories of growing-season cover are assumed to be consistent from season to season, but this assumption has not been tested.

### Example Results

The following are examples of early findings and preliminary analyses based on various FIA surveys that have documented the presence of invasive plants. Some of this information is taken from upcoming reports of P2 and P3 nonnative vegetation surveys for selected areas of the United States. We also include selected information from FIA survey data archives dating from the 1990s and earlier.

#### Distributions of Invasive Species

Managers and scientists derive their knowledge of distributions of invasive plant species from observations for a range of earth cover types. At present, inferences about species distributions typically rely on information stored at state and national herbaria, which contain physical records for an array of earth cover types. These records, unlike FIA records, rarely reference periodic, systematic observations or comprehensive environmental, spatial, or temporal details for broad areas. Inferences from FIA obser-

vations of invasive species, however, are generally limited to forest land. FIA's sampling design and measurement protocols have been adapted to nonforest areas (O'Brien *et al.* 2003, Riemann 2003), but cost and the logistical difficulties in collaborating with agencies responsible for nonforest land assessments are impediments to wider adoption of these methods.

Combining FIA data with data from other sources can increase our knowledge of invasive plant species distributions. Figure 2a illustrates P2 FIA data from county surveys of forest land from

four southern States (Georgia, North Carolina, South Carolina, and Virginia) that are infested with Japanese honeysuckle. (Note that the FIA data represented in the example is for only about 1/5 of the sample plots.) Figure 2b shows corresponding county-level data from the PLANTS Database of herbarium records (USDA NRCS 2004). By combining the two sources, one obtains a more comprehensive account of the range and counties occupied (fig. 2c).

## P2 Infestation and Severity Estimates

The summary of invasive plant occurrences on P2 forest land plots includes information about infestations by one or more selected species for the States represented (table 2). Without accounting for sample size and observer variability by State, species, and infestation severity, regional differences in the frequency of plots with invasive plants appear large. For example, 72 percent of forest land is infested in Kentucky, while 23 percent of forest land is infested in Arkansas. The preliminary conclusion is that varying climate and forest disturbance regimes favor one or more species in the target species list. To suggest that forest land in Arkansas is less susceptible to plant invasions, and Kentucky is more susceptible, is tempting, but not valid without an assessment of all vascular species.

In the areas surveyed for invasive plant species on the South's target list, Japanese honeysuckle infests the most forest land, with Chinese and European privet (*Ligustrum sinense*, *L. vulgare*) ranked a distant second (table 3). Kudzu is ranked 14<sup>th</sup> in overall frequency, but kudzu outranks the other 13 taxa in the

Figure 2.—Japanese honeysuckle distribution by county in Georgia, North Carolina, South Carolina, and Virginia: (a) FIA phase 2 field observations, 2001–04, (b) PLANTS Database 2002, largely from herbarium specimens, and (c) both combined: information from (b), with additions from (a).

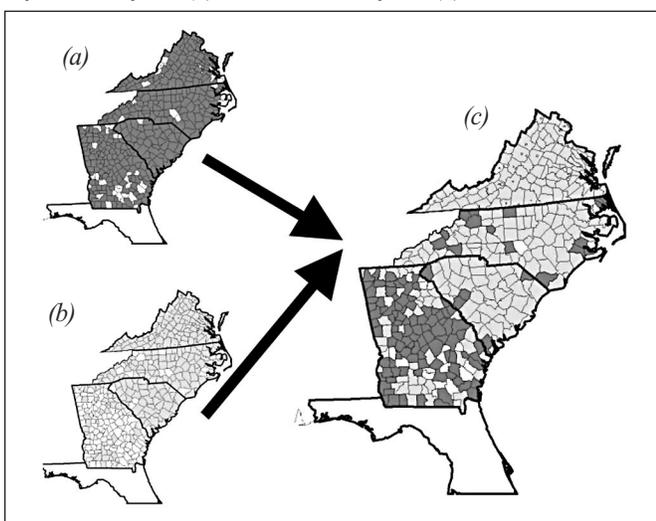


Table 2.—Sampled locations with forest land and percent infested by State, 2001–04, as of September 2004.<sup>a</sup>

Attribute	All States	Arkansas	East Texas	South Carolina	Louisiana	North Carolina	Georgia	Virginia	Tennessee	Alabama	Kentucky
Number of forest land plots	10,368	639	2,202	484	955	711	597	638	1,552	1,681	909
Percent infested with one or more of 33 taxa	49	23	40	41	42	47	50	51	53	63	72

<sup>a</sup> Data are from completed panels in the South (as of September 2004) and represent a portion of the final 5-km sample grid intensity. States, panel numbers, and approximate proportions are: Arkansas, 3, 0.20; East Texas, 1 through 5, 1.00; South Carolina, 4, 0.20; Louisiana, 4 and 5, 0.40; North Carolina, 5, 0.20; Georgia, 3, 0.14; Virginia, 4, 0.20; Tennessee, 3, 4, and 5, 0.60; Alabama, 3 and 4, 0.40; and Kentucky, 3 and 4, 0.33.

Table 3.—Relative frequency of infested forest land subplots by taxa and State, 2001–04, for panels completed as of September 2004.<sup>a</sup>

Attribute	All States	Arkansas	East Texas	South Carolina	Louisiana	North Carolina	Georgia	Virginia	Tennessee	Alabama	Kentucky
		<i>Relative frequency</i>									
Japanese honeysuckle	50	77	41	62	25	58	62	50	54	66	31
Chinese and European privet	11	1	11	10	13	14	25	6	5	19	0
Chinese tallowtree	7	0	31	2	26	0	1	0	0	1	0
Tall fescue	6	0	0	3	0	0	0	15	5	0	25
Nonnative roses	6	2	1	0	0	9	0	8	7	0	20
Japanese/glossy privet	5	14	5	8	8	6	2	3	8	6	0
Japanese climbing fern	3	0	5	0	23	0	1	0	0	2	0
Bush honeysuckles	3	0	0	0	0	2	0	3	2	0	11
Tree-of-heaven	2	0	0	1	0	1	0	7	4	0	3
Chinese lespedeza	2	3	0	5	0	3	6	2	2	0	2
Nepalese browntop	1	0	0	0	0	1	0	0	6	0	1
Mimosa	1	2	2	0	1	1	1	0	1	2	0
Chinaberry	1	0	2	1	1	0	2	0	0	1	0
Kudzu	1	1	0	1	0	0	1	0	0	2	0
15 other taxa	4	0	1	6	2	6	1	5	6	2	6
All taxa	100	100	100	100	100	100	100	100	100	100	100
Number of infested subplots	17,362	343	2,473	598	1,329	1,049	1,014	1,195	2,909	3,726	2,726
$\sum(\text{\#subplots})_{\text{taxa}}$											

<sup>a</sup> Data are from completed panels in the South (as of September 2004) and represent a portion of the final 5-km sample grid intensity. States, panel numbers, and approximate proportions are: Arkansas, 3, 0.20; East Texas, 1 through 5, 1.00; South Carolina, 4, 0.20; Louisiana, 4 and 5, 0.40; North Carolina, 5, 0.20; Georgia, 3, 0.14; Virginia, 4, 0.20; Tennessee, 3, 4, and 5, 0.60; Alabama, 3 and 4, 0.40; and Kentucky, 3 and 4, 0.33.

severity of its infestations (fig. 3). Thirty-one percent of kudzu-infested subplots have greater than 50 percent coverage, which means that kudzu is the dominant species in these subplots.

The strength of FIA's probability-based sampling design is that one is able to make inferences about the extent of infestations and their severity on forest land. An east Texas example shows that Japanese honeysuckle infests 2,774,900 acres, which make up 23 percent of the region's 12 million forest land area in

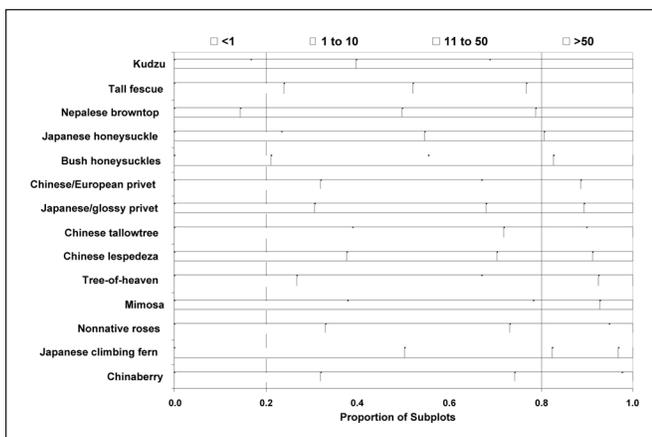
2003. Statistically, one may be 95 percent confident that the area is between 2,838,600 and 2,711,200 acres, or  $2,774,900 \pm 63,700$ . Confidence in estimates is strong for the common species and weak for rarely occurring species such as kudzu (table 4). In general, estimates of total cover represent less than 10 percent of the infected area of forest land. Japanese honeysuckle infests a million more acres than Chinese tallowtree (*Triadica sebifera*), a canopy-dominant tree species, but the two species are statistically similar in terms of total cover.

Table 4.—Top 12 invasive species infesting forest land and their severity, east Texas, 2001–03 surveys.

Species	Infested forest land			Severity (total cover)	
	% of total forest land	Acres (1,000s)	95% confidence interval	Acres (1,000s)	95% confidence interval
Japanese honeysuckle	22.9	2,774.9	±63.7	154.7	±15.0
Chinese tallowtree	14.1	1,715.3	±50.1	160.0	±15.3
Chinese/European privet	5.8	701.3	±32.0	39.1	±7.6
Japanese/glossy privet	3.4	413.4	±24.6	17.7	±5.1
Japanese climbing fern	3.0	369.1	±23.2	12.6	±4.3
Chinaberry	2.3	281.6	±20.3	8.5	±3.5
Mimosa	1.5	182.9	±16.4	1.7	±1.6
Chinese lespedeza	0.5	54.6	±8.9	0.1	NA
Nonnative roses	0.4	52.6	±8.8	1.9	±1.7
Bush honeysuckles	0.3	40.5	±7.7	1.7	±1.6
Nandina	0.3	39.2	±7.6	0.5	NA
Kudzu	0.3	33.4	±7.0	0.4	NA

NA = Confidence interval includes zero.

Figure 3.—Proportion of infested subplots by species and severity class (< 1, 1–10, 11–50, and > 50 percent cover) for panels completed as of September 2004, southern United States.



### P3 Sampling

The census of all vascular species from P3 forest land observations provides information that is being used to develop indicators of forest health. Part of this development includes documenting their legitimacy, e.g., assurance in species identification (Gray and Azuma 2005). At present, funding for full implementation of all vascular vegetation on P3 plots is uncertain. The 1,300 plot observations of all vascular vegetation on forest land between 2001 and 2003 have been made only in selected States and survey years (table 5).

Table 5.—Number of sampled plots on forest land in the conterminous United States for 2001–03 in which an all-vascular species inventory was conducted, by FIA region, State, and year. Unless otherwise noted, sampling was at the P3 (22-km) grid density.

FIA region and State	2001	2002	2003
	Number		
<b>Interior West</b>			
Utah	40	45	50
<b>Northeastern</b>			
Delaware <sup>a</sup>	19	19	21
Ohio	16	21	26
Pennsylvania <sup>a</sup>	136	99	33
New Jersey <sup>a</sup>	9	6	0
New York <sup>a</sup>	21	10	0
<b>North Central</b>			
Illinois	14	8	17
Indiana	12	6	7
Iowa	7	9	5
Kansas	8	6	6
Michigan	41	43	43
Minnesota <sup>a</sup>	70	70	42
Missouri	36	32	35
Nebraska	4	5	2
North Dakota	3	0	1
South Dakota	4	3	4
Wisconsin	34	32	29
<b>Pacific Northwest</b>			
Oregon	62	0	0
<b>Southern</b>			
South Carolina	0	31	0
<b>Total</b>	<b>536</b>	<b>445</b>	<b>321</b>

<sup>a</sup> Included samples at the P2 (5-km) grid density for special study areas, such as the Allegheny National Forest.

P3 sampling serves to corroborate species ranking from P2 plot observations, includes vouchered specimens deposited at regional herbaria for future study, and fills in information gaps associated with narrower target lists. In South Carolina, a pilot study of P3 data collection notes nonnative species occurred in an average of 5 percent of 31 forest land plots (Oswalt, in press). As with P2 observations, Japanese honeysuckle is the overall dominant invasive species by frequency, and kudzu is relatively rare. Included among recorded invasive species are the less easily identifiable life forms such as grasses, e.g., Bermudagrass (*Cynodon dactylon*), and species such as alligatorweed (*Alternanthera philoxeroides*), which are problems only in uncommon, specialized habitats, such as forested wetlands with limited tree cover.

Analysis of P3 indicators include the proportions of species richness and cover in introduced species, and these estimates serve as measures of relative impact (Stapanian *et al.* 1998). For example, Gray and Azuma (2005) note that the proportions of nonnative to native-and-introduced vascular plant species richness and cover differed significantly by ecoregion in forest land of western Oregon.

An illustration comes from a preliminary examination of P3 observations for the North Central FIA region (fig. 4) which suggests that the proportion of nonnative plant species varies by

ecoregion (Olson *et al.* 2003). Large blocks of forest land—predominantly evergreen forest types—are associated with lower nonnative proportions. One interpretation is that the proportion varies directly with landscape-scale disturbances, such as forest fragmentation, and regional soil fertility. Another is that regions predominantly in deciduous forest land may be more susceptible to invasion by semi-evergreen species with longer growing cycles than regions predominantly in evergreen forests. Elsewhere, preliminary data appear to corroborate these patterns (Olson *et al.* 2003; Oswalt, in press; Schulz and Gray 2004).

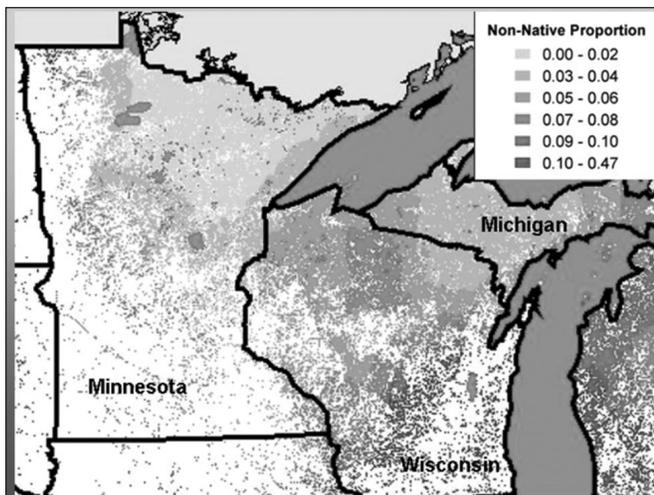
### Opportunities for Further Analysis

On forest land, future analysis of P2 and P3 observations will increase when monitoring of invasive plant species is fully implemented and standardized across FIA regions. Such analyses will permit a broader national understanding of pest species populations and their potential threat across all regions.

Robust risk assessments require national coordination, augmented interagency cooperation, and transdisciplinary collaboration with other monitoring efforts. These include national programs responsible for areas outside forest land, e.g., the USDA NRCS National Resources Inventory, State and local monitoring for management operations (Carpenter *et al.* 2002), and invasive species observations by volunteers (e.g., Brown *et al.* 2001).

In Alaska, one coordinated approach includes the establishment of an interagency memorandum of understanding, a strategy for cooperative inventories (Shephard *et al.* 2002), and an associated Web site (Alaska Committee for Noxious and Invasive Plants Management 2004). Another is the report from The H. John Heinz III Center for Science, Economics and the Environment (2002) and a newly launched Web site that focuses on invasive species (National Institute of Invasive Species Science, n.d.). The institute is in the process of gathering knowledge about invasive plant species from various agencies and land cover types, and analysts may one day be able to use the Web site's assembled data to supplement FIA forest land observations when developing risk prediction models with wider applicability.

Figure 4.—Percent nonnative species on forest land by ecoregion, Michigan, Minnesota, and Wisconsin (Source: Olson *et al.* 2004).



### Analyses With Older Survey Data

Before establishment of the P3 national sampling protocol for vascular plants and regional P2 sampling protocols for invasive plant species, a few FIA regions surveys estimated vegetation structure on timberland by easily distinguished plant taxa.

These surveys happened to include a few invasive plant species in their tally. We highlight ongoing and recently completed analyses of these older data as example information products that could be developed from data currently being collected. The FIA program could generate similar information for all forest land if national P2 standard protocols for species selection and field measurement were established, and if the national form of P3 sampling were implemented across the United States.

One example analysis provides estimates of Himalayan (*Rubus discolor*) and cutleaf blackberry (*R. laciniatus*) based on the 1998 western Oregon forest survey of non-federal land. Gray (2005) used stepwise logistic regression of these species' distributions to construct a model with correlated variables and thereby obtain an understanding of likely causal variables. Although model predictability was generally less than 50 percent, analyses and associated maps supported hypotheses that invasions were more likely at low elevations and in timberland with limited overstory cover (tree basal area, crown cover).

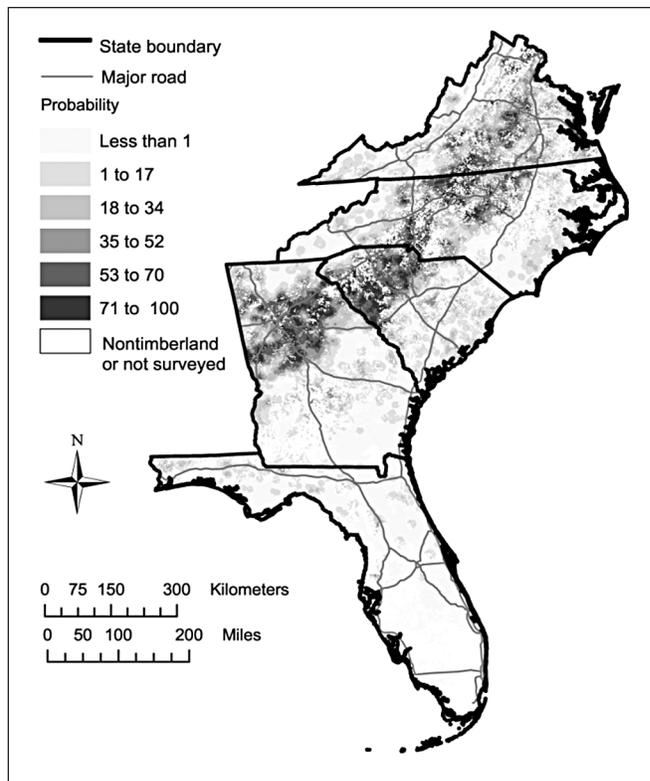
Another analysis yields maps of infestation probabilities for a few well-known species and is based largely on interior forest surveys of understory species in Southeastern United States timberland during the 1990s. Findings noted infestation probabilities are greater for Japanese honeysuckle in the Southern Mixed Forest than Coastal Plain provinces (fig. 5). For more details about the interpolation, see Jacobs and Rudis (2005).

Data came from interpolations of presence-absence observations recorded in a 1989–95 survey of 26,882 timberland sample locations<sup>2</sup>. About 20 percent of the forest sample locations were infested with Japanese honeysuckle, 3.5 percent with privet (*Ligustrum* spp.), 0.9 percent with multiflora rose (*Rosa multiflora*), and 0.2 percent with kudzu. The odds of infestation probability were greatest with the absence of prescribed fire. Trends based

on matched locations (timberland for both the 1980s and 1990s surveys) indicated a statistically significant decline in infestation probability over the decade for Japanese honeysuckle, no change in kudzu, and an increase in privet.

A third example characterizes forest fragmentation and the odds of infestation relative to the forest edge by employing the fixed configuration of the current plot design. Of 6,761 sampled forest locations in the 1997 survey of Georgia's timberland, 9 percent contained forest-nonforest edges<sup>2</sup>. The odds of an infestation by Japanese honeysuckle were two times greater, for privet three times greater, and for kudzu seven times greater at the forest edge than in forest interior locations. Forest land in nonforest-dominated neighborhoods may be particularly vulnerable to invasion due to the close proximity to anthropogenic activities and likely larger invasive plant populations on nonforest land (Franklin *et al.* 2003).

Figure 5.—*Infestation probability of Japanese honeysuckle on timberland, southeastern United States.*

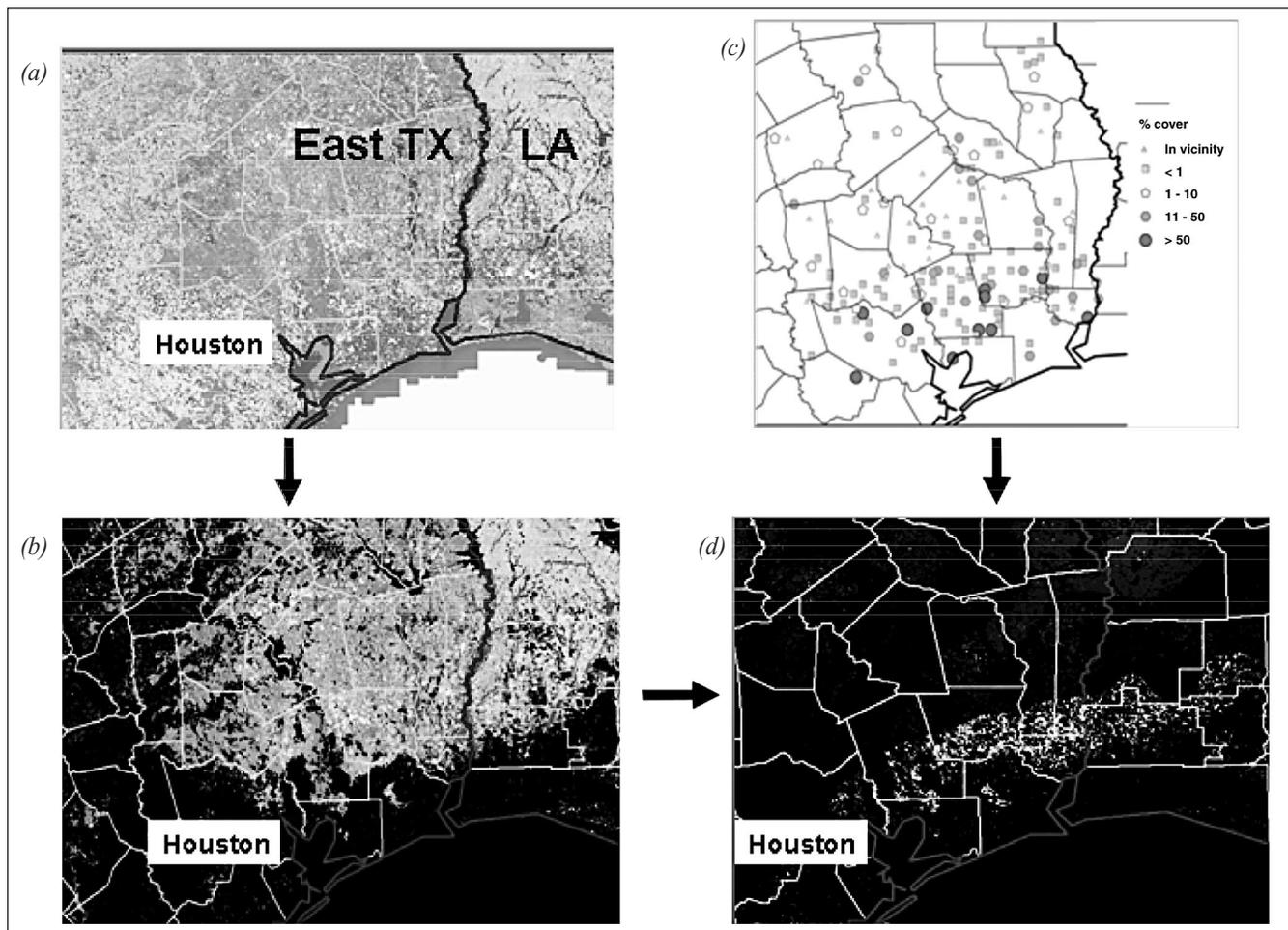


<sup>2</sup> Data on file with: USDA Forest Service, FIA Program, 4700 Old Kingston Pike, Knoxville, TN 37919.

Fine-scaled, spatially referenced estimates of invasive species often are the data of most interest to county and other local land managers. This fourth example describes a protocol for obtaining fine-scale, spatially-registered estimates for Chinese tallowtree, a species noted in surveys conducted in the south central United States beginning with 1990s surveys. Figure 6 illustrates portions of the protocol. Initial efforts require geographic registration of satellite imagery to FIA plot locations containing a single condition, and all four subplots are completely forested or completely nonforested. The next step develops a model that predicts forest land and nonforest land based on sampled values; secondary data from other sources also are employed as predictors. Figure 6b illustrates results using

Moderate Resolution Imaging Spectroradiometer (MODIS) imagery to predict forest land at 250-m resolution. The third step develops a predictive model of invasive species presence and biomass volume for standing trees. In addition to FIA plot and forest condition information, the model may include other geographically registered data, such as generalized ecoregion boundaries, specific climate attributes from the National Weather Service, slope and elevation estimates from the U.S. Geological Survey, and soil properties from the NRCS Natural Resources Inventory. The final model yields a map of satellite image spectral values that estimate the species' biomass volume at 250-m resolution. For Chinese tallowtree, biomass values may appear something like those displayed in figure 6d.

Figure 6.—Steps in the process of fine-scaled estimation of Chinese tallowtree biomass: (a) MODIS satellite imagery at 250-m resolution for east Texas and west Louisiana; (b) spectral value classification of forest and nonforest land; (c) Chinese tallowtree-infested FIA forest land sample locations in east Texas by presence and infestation severity (percent total cover); and (d) depiction of Chinese tallowtree biomass at 250-m resolution.



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Analysts can test the underlying predictions against other FIA observations withheld from initial model development. The final map product, together with associated reliability statistics, provides sufficient spatial resolution for more detailed planning by county-level managers.

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## Appendix

This list contains the inventoried invasive species on Forest Inventory and Analysis (FIA) forest plots in the conterminous United States.

### Trees

#### National (Core-required)

- Tree-of-heaven<sup>†b</sup> *Ailanthus altissima*
- Tung-oil tree *Aleurites fordii*
- Mimosa, silk tree<sup>†</sup> *Albizia julibrissin*
- European alder *Alnus glutinosa*
- Eucalyptus *Eucalyptus* spp.
- Melaleuca<sup>‡</sup> *Melaleuca quinquenervia*
- Chinaberry<sup>\*</sup> *Melia azedarach*
- Royal paulownia *Paulownia tomentosa*
- Mesquite<sup>‡</sup> *Prosopis* (selected species, not *P. glandulosa*, *P. pubescens*, *P. velutina*)
- European mountain ash *Sorbus aucuparia*
- Chinese tallowtree<sup>†</sup> *Triadica sebifera* (*Sapium sebiferum*)
- Siberian elm *Ulmus pumila*

#### National (Core-optional)

- Norway maple *Acer platanoides*
- Camphortree<sup>†</sup> *Cinnamomum camphora*
- Russian olive<sup>\*b</sup> *Elaeagnus angustifolia*
- Saltcedar<sup>a,b</sup> *Tamarix* spp.

### Shrubs

#### North Central

- Japanese barberry<sup>†</sup> *Berberis thunbergii*
- Glossy buckthorn *Frangula alnus*
- Common buckthorn *Rhamnus cathartica*

#### North Central, Southern

- Autumn olive<sup>†</sup> *Elaeagnus umbellata*
- European privet<sup>†c</sup> *Ligustrum vulgare*
- Bush honeysuckles<sup>†</sup> *Lonicera* spp.
- Multiflora rose<sup>†</sup> *Rosa multiflora*

#### Pacific Northwest

- English holly<sup>c</sup> *Ilex aquifolium*
- Himalayan blackberry<sup>b,c</sup> *Rubus discolor*
- Cutleaf blackberry<sup>c</sup> *Rubus laciniatus*
- Scotch broom<sup>b,c</sup> *Cytisus scoparius*
- Gorse<sup>b,c</sup> *Ulex europaeus*

#### Southern

- Silverthorn<sup>\*</sup> *Elaeagnus pungens*
- Winged euonymus, burning bush, *Euonymus alata*
- Chinese privet<sup>†</sup> *Ligustrum sinense*, Japanese privet<sup>†</sup> *L. japonicum*, glossy privet<sup>†</sup> *L. lucidum*
- Nandina, sacred bamboo<sup>\*</sup> *Nandina domestica*
- Nonnative roses *Rosa* spp.

#### Ferns—Southern

- Japanese climbing fern<sup>†</sup> *Lygodium japonicum*

### Forbs/Herbs/Other Herbaceous

#### Interior West

- Russian knapweed<sup>b,c</sup> *Acroptilon repens*
- Hoarycress<sup>b,c</sup> *Cardaria draba*
- Diffuse knapweed<sup>b,c</sup> *Centauria diffusa*

#### Interior West, North Central

- Leafy spurge<sup>b,c</sup> *Euphorbia esula*

<sup>\*</sup> Species introduction on national forest land discouraged (Southeast Exotic Pest Plant Council 2001).

<sup>†</sup> Species introduction on national forest land prohibited (Southeast Exotic Pest Plant Council 2001).

<sup>‡</sup> Species on the Federal Noxious Weed List (Federal Register 2004).

<sup>a</sup> Surveyed as a tree only in the Interior West.

<sup>b</sup> Species present and representing a potential threat to the Sierra Nevada National Forest (USDA Forest Service, Pacific Southwest Region 2001).

<sup>c</sup> Species introduction on national forest land prohibited (USDA Forest Service, Pacific Northwest Region 2004).

### Interior West, North Central, Pacific Northwest

- Thistle<sup>\*,b,c</sup> *Cirsium* spp.

### North Central

- Common burdock *Arctium minus*
- Japanese knotweed<sup>†c</sup> *Polygonum cuspidatum*
- Mile-a-minute weed<sup>\*</sup> *P. perfoliatum*

### North Central, most of Interior West

- Spotted knapweed<sup>c</sup> *Centauria bierbersteinii*

### North Central, Southern

- Garlic mustard<sup>†</sup> *Alliaria petiolata*

### Pacific Northwest

- **NFS California:**
  - Musk thistle<sup>\*,b,c</sup> *Carduus nutans*
  - Knapweed<sup>b,c</sup> *Centauria diffusa*,  
*C. solstitialis*, *C. maculosa*<sup>\*</sup>
  - Rush skeleton weed *Chonrilla juncea*
  - Spurge<sup>b,c</sup> *Euphorbia esula*, *E. oblongata*
  - French broom<sup>b,c</sup> *Genista monspessulana*
  - Medusa head<sup>b,c</sup> *Taeniatherum caputmedusa*
- Foxglove<sup>c</sup> *Digitalis purpurea*
- Wall lettuce *Mycelis muralis*

### Pacific Northwest United States and Colorado, Montana, Nevada, and Wyoming

- St. Johnswort<sup>b,c</sup> *Hypericum perforatum*

### Southern

- Shrubby lespedeza *Lespedeza bicolor*

### Southern United States and Arizona

- Chinese lespedeza<sup>†</sup> *Lespedeza cuneata*
- Tropical soda apple<sup>†</sup> *Solanum viarum*

## Grasses

### North Central

- Reed canary grass<sup>c</sup> *Phalaris arundinacea*
- Common reed *Phragmites australis*

### North Central, Southern

- Nepalese browntop<sup>†</sup> *Microstegium vimineum*

### Southern

- Giant reed *Arundo donax*
- Tall fescue<sup>†</sup> *Lolium arundinaceum*
- Cogongrass<sup>†</sup> *Imperata cylindrica*
- Chinese silvergrass<sup>\*</sup> *Miscanthus sinensis*
- Nonnative bamboos *Phyllostachys* spp., *Bambusa* spp

## Vines

### Pacific Northwest, Southern

- English ivy<sup>\*,c</sup> *Hedera helix*

### North Central

- Porcelainberry<sup>\*</sup> *Ampelopsis brevipedunculata*
- Black swallowwort *Cynanchum louiseae*

### North Central, Southern

- Oriental or Asian bittersweet<sup>†</sup> *Celastrus orbiculatus*
- Nonnative climbing yams –air yam/Chinese yam/water yam<sup>†</sup> *Dioscorea bulbifera*/*D. oppositifolia*/*D. alata*
- Wintercreeper<sup>†</sup> *Euonymus fortunei*
- Japanese honeysuckle<sup>†</sup> *Lonicera japonica*
- Kudzu<sup>†</sup> *Pueraria montana*

### Southern

- Periwinkles<sup>c</sup> *Vinca minor*, *V. major*
- Chinese/Japanese wisteria<sup>\*</sup> *Wisteria sinensis*/*W. floribunda*

<sup>\*</sup> Species introduction on national forest land discouraged (Southeast Exotic Pest Plant Council 2001).

<sup>†</sup> Species introduction on national forest land prohibited (Southeast Exotic Pest Plant Council 2001).

<sup>‡</sup> Species on the Federal Noxious Weed List (Federal Register 2004).

<sup>b</sup> Species present and representing a potential threat to the Sierra Nevada National Forest (USDA Forest Service, Pacific Southwest Region 2001).

<sup>c</sup> Species introduction on national forest land prohibited (USDA Forest Service, Pacific Northwest Region 2004).

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## Florida Supplement

### Florida Trees

- Australian-pines *Casuarina spp.*
- Carrotwood *Cupaniopsis anacardioides*
- Schefflera *Schefflera actinophylla*
- Java plum *Syzygium cumini*

### Florida Subshrubs

- Coral ardisia<sup>†</sup> *Ardisia crenata*
- Lantana *Lantana camara*

### Florida Shrubs

- Surinam cherry *Eugenia uniflora*
- Guava spp. *Psidium spp.*
- Downy rose myrtle<sup>†</sup> *Rhodomyrtus tomentosa*
- Brazilian pepper<sup>†</sup> *Schinus terebinthifolius*
- Wetland nightshade<sup>‡</sup> *Solanum tampicense*

### Florida Vines

- Rosary pea *Abrus precatorius*
- Cat's-claw vine<sup>†</sup> *Macfadyena unguis-cati*
- Skunk vines<sup>†</sup> *Paederia spp.*

### Florida Grasses

- Napier grass *Pennisetum purpureum*

### Florida Ferns

- Smallleaf climbing fern<sup>†</sup> *Lygodium microphyllum*
- Sword fern *Nephrolepis cordifolia*

### Florida Forbs/Herbs/Other Herbaceous

- Hairy indigo *Indigofera hirsuta*

Not included are lists used in special studies supported in part by cooperating agencies. For example, the Northeastern FIA uses an extended list of nonnative tree species in special surveys of urban and other nonforest land (Riemann 2003), and conducts an ongoing, growing-season survey to assess cover for 12 invasive species, and occurrence for 38 others in Pennsylvania. In the West, special surveys in selected western national forest districts and regions include noxious species surveys on nonforest land, e.g., Bridger-Teton National Forests (O'Brien *et al.* 2003).

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\* Species introduction on national forest land discouraged (Southeast Exotic Pest Plant Council 2001).

† Species introduction on national forest land prohibited (Southeast Exotic Pest Plant Council 2001).

‡ Species on the Federal Noxious Weed List (Federal Register 2004).

## Drought-Related Mortality in Pinyon-Juniper Woodlands: A Test Case for the FIA Annual Inventory System

John D. Shaw<sup>1</sup>

**Abstract.**—Several years of drought in the Southwest United States are associated with widespread mortality in the pinyon-juniper forest type. A complex of drought, insects, and disease is responsible for pinyon mortality rates approaching 100 percent in some areas, while other areas have experienced little or no mortality. Implementation of the Forest Inventory and Analysis annual inventory approximately coincided with the beginning of the mortality event, providing an opportunity to use the event as a test case for the annual inventory system. Preliminary analysis suggests that annual inventory data can quantify status and trends. Some findings will be verified using aerial imagery and independent ground inventory data.

In the mid-1990s, the U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) program began a shift from a periodic to an annual inventory system (Gillespie 1999). Under the periodic system, plots were measured over the entire sample grid in a given State over a period of 1 to several years. The planned revisitation cycle in the Western United States was 10 years, but actual cycle lengths sometimes approached 20 years. FIA data and reports produced by periodic

inventories became increasingly outdated. In response to user demand for more timely information, the FIA program began to test and implement an annual inventory system in 1996 (Gillespie 1999).

The annual inventory system uses essentially the same systematic sample grid that was used for periodic inventories, with 1/10<sup>th</sup> of the plots in a State sampled in any given year. Plots are distributed throughout the State in each annual panel—i.e., the entire grid is used each year, and the plots are shifted on the grid from year-to-year. As a result, annual panels are theoretically free from geographic bias. Under this system, data are available every year, and reporting is intended to occur after 50 percent of the plots (five annual panels) in a State have been sampled.

The Interior West FIA (IWFIA) program—which is responsible for Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming—implemented the annual inventory system in 2000 in Utah and has added most other States since then (table 1). About the same time that annual inventory was started in the Interior West, forest managers and researchers began to notice an increase in the incidence of insects and disease in some forest types. Some of these effects were attributed to the drought that spread across the Southwest beginning in the late 1990s.

Table 1.—Year of last periodic inventory and implementation of annual inventory for IWFIA States.

State	Last periodic	First annual	State	Last periodic	First annual
Arizona	1999	2001	New Mexico	2000	tbd <sup>b</sup>
Colorado	1983	2002	Montana	1989	2003
Idaho	1991	2004	Utah	1994	2000
Nevada	1989	2004 <sup>a</sup>	Wyoming	1983	tbd

<sup>a</sup> Research pilot inventory approximating an annual panel.

<sup>b</sup> tbd = year of first annual inventory to be determined.

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At the writing of this article, the drought is ongoing, and significant drought-related mortality has been observed in several forest types across the Southwest. Among the most seriously affected are the ponderosa pine and pinyon-juniper types. Widespread and locally severe mortality in these types has led to several efforts to quantify the effects of drought, insects, and disease over the past 5 years. Most of these efforts have been ad hoc or local in nature and lack the geographic and temporal ranges covered by the FIA program. Therefore, the current mortality event can be considered an opportunistic test of the utility of the FIA annual inventory system for quantifying rapid change over a large geographic area. Analysis of the event may also test some assumptions that have been made or concerns that have been expressed about the FIA annual inventory system.

This article describes the geographic distribution of FIA data obtained before and during the mortality event, preliminary analysis of the results, and how the design of the annual inventory system may affect the final analysis.

## Drought and Effects on Forests

Onset of the drought currently experienced across the Southwest occurred about 1998 (McPhee *et al.* 2004), but the exact time of onset varies by location and interpretation of climatic data. In the spring of 2003 a “Drought Summit” was held in Flagstaff, AZ, bringing together a wide variety of experts from across the Southwest. At that time, some suggestions were made that the drought could become a 1-in 500-year, or even an unprecedented, event. But it now appears that the current drought is comparable in magnitude to the early 1900s drought, the 1950s drought, and many other dry periods that have been documented by tree-ring-based reconstructions of the past 800 years (Cole *et al.* 2004, MCPhee *et al.* 2004). As of December 2004, it appears that some areas affected by drought since the late 1990s are experiencing some relief (Society of American Foresters 2004).

Anecdotal reports of drought-related effects on Southwest forests began in 2000, but a dramatic increase in tree mortality

occurred in 2002 (Anhold and McMillin 2003). Local reports noted up to 100 percent mortality in ponderosa pine and pinyon-juniper forest types, such as in the Horsethief Basin and San Francisco Peaks areas of Arizona. A rapid increase in the extent of high-mortality areas was recorded by aerial surveys between the fall of 2002 and the fall of 2003 (Anhold and McMillin 2003). Estimates of 90-percent or greater mortality over large areas continue to be reported (e.g., Society of American Foresters 2004), but the exact extent of high-mortality areas has not yet been completely documented.

The primary agents responsible for tree mortality in the Southwest were the western pine beetle (*Dendroctonus brevicomis* LeConte) in ponderosa pine, and the pinyon ips beetle (*Ips confusus* LeConte) in pinyon pine. A variety of other insects and diseases also affected these and other tree species, and a comprehensive list of possible agents has yet to be completed. Hereafter in this article, mortality will refer to that caused by a complex of drought, insects, and disease, excluding fire and other causes.

In early 2003, the USDA Forest Service Interior West Forest Health Monitoring (FHM) Regional Program Manager requested a preliminary analysis of FIA annual inventory data as a supplement to ongoing FHM assessments. The preliminary assessment focused on Arizona and Utah, for which 2 and 3 years of annual inventory data were available, respectively. The data suggested a modest increase in mortality of pinyon and juniper species in 2002, but the percentage of total basal area affected was still relatively small. At that point, in part due to the fact that estimated mortality (based on annual data only) was near zero in 2000 and 2001, whether the apparent increase was signal or noise was not clear. The prospect of using data from annual FIA panels as time series data raised several important questions, some of which had been discussed in detail when the move from a periodic to annual inventory system was considered, and some of which are still subjects of active research. The nature of the mortality event—widespread, patchy, and increasing over time—and the questions raised by attempts to quantify it using annual FIA data suggested that the event could be used as an ideal test of the FIA annual inventory system.

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## Questions About FIA Inventory Design and Reporting

The first set of questions relates to FIA inventory design, in terms of the number and design of plots. First and most fundamentally, are there enough plots in one annual panel to detect the progression of the mortality event? FIA periodic inventories are sampled on a grid, with one potential field plot for approximately every 6,000 acres (known as phase 2). Under annual inventory, approximately 9,500 phase 2 plots are in Utah, about 3,700 of which are expected to occur in forest conditions. This means that approximately 370 plots (1/10<sup>th</sup> of the forested phase 2 plots) across the State are scheduled to be visited in any given year. Pinyon-juniper is the most common forest type in most of the States in which it occurs. Of the 370 plots to be visited annually in Utah, 160 to 180 are expected to sample the pinyon-juniper type. The proportions given for Utah are comparable to other States with significant acreage of the pinyon-juniper type (Arizona, Colorado, New Mexico, and Nevada).

Stand densities commonly found in the pinyon-juniper type span the low end of stocking that meets the definition of forest for the purpose of FIA inventory. The most recent periodic inventories and all annual inventories use the new mapped-plot design, which consists of a cluster of four 1/24-acre subplots (Scott and Bechtold 1995). Given the sparse nature of the pinyon-juniper type, asking whether enough trees are tallied on plots in very sparse stands to adequately represent the site is a reasonable question. In addition, mortality may be quite patchy within stands, raising the possibility that only green trees may be sampled in a landscape that is clearly experiencing significant mortality.

Potential users of FIA data who are interested in the causes of mortality often raise questions about identification of causal agents. Although FIA maintains an extensive quality control program, the nature of the mortality event is such that primary causes may be obscured. Drought-related mortality has been characterized as a complex of drought, insects, and disease, and two or more agents are likely to be present on the plot (although drought is assumed to be ubiquitous at present, ground crews do not measure it). In addition, the mortality trees are defined as those judged to have died in the 5 years before the

current inventory. The possible lag between time of death and measurement allows for the loss of evidence of the primary agents or invasion of secondary agents factors. This may lead to the recording of “unknown” as the cause of death by the field crew because the cause is not discernible or several likely causal agents exist.

Questions related to analysis and reporting are also of concern. FIA statisticians are currently researching the implications of several methods of compiling annual data, such as methods of combining panels to reduce variance (Patterson and Reams, 2005). Under normal circumstances, the combination of multiple annual panels may not be a significant issue. In the event of catastrophic change—fire and hurricanes being commonly cited examples—the catastrophe has relatively identifiable boundaries, and affected plots can be stratified to reduce variance. By all accounts, however, drought-related mortality in the pinyon-juniper type is a population-scale phenomenon. Although locally concentrated in some cases, mortality appears to occur patchily across the landscape. These two characteristics may make stratification of affected and unaffected plots difficult or impossible.

In addition to the variance issue, a concern exists over lag and smoothing effects created by combining panels. Patterson and Reams (2005) describe two methods of combining panels that may be used in FIA analyses—moving averages and temporally indifferent combination. Both methods can produce a time lag bias when the variable of interest exhibits unidirectional change over time. The magnitude of the bias depends on the length of time over which panels are combined and the rate of change over time. For some variables, lag and smoothing effects may be minor and offset by the reduction in variance produced by combining panels. Patterson and Reams (2005), however, note that “in the presence of a widespread catastrophic event, lag bias cannot be ignored.”

Analysis of annual inventory data may have some limitations due to the reduction in sample size caused by dividing the phase 2 grid by the number of annual panels. The combination of plots over space, as well as combining panels over time, will tend to reduce variance. In this case, the tradeoff is between geographic extent and variance as opposed to temporal currency

and variance. This tradeoff raises questions regarding the appropriate scale at which estimates can be made with reasonable confidence. Because of the limitations in the data, these scales may or may not be satisfactory from some users' perspectives.

## Addressing the Questions

As a naturally occurring experiment, the drought-related mortality event provides an opportunity for addressing some of the questions that surround the FIA annual inventory system. The widespread nature of the event has drawn interest from a broad group of managers and researchers, some of whom have experience with the FIA program. In response to increasing mortality across the Southwest, non-FIA entities inside and outside the USDA Forest Service implemented short-term inventory and monitoring projects. Two organizations in the Forest Service—the Forest Health Technology Enterprise Team (FHTET) and Region 4 Forest Health Protection (FHP)—approached the IWFA program requesting data on pinyon-juniper forests for use in designing their own studies. Based on the planned design of the studies, closer coordination could benefit all organizations involved. From the FIA perspective, the primary benefit would be to produce data that could be used to address some of the questions stated above, thereby testing the annual inventory system. As a result, cooperative agreements were established, and both studies were implemented as adjunct inventories using FIA phase 2 plot locations.

The FHTET study involved acquisition of high-resolution, digital color infrared imagery over plots in the pinyon-juniper type in late 2003. Plot locations were selected using a random sample

of plots from the 2003 annual panel that were classified as pinyon-juniper. For each selected plot, the nearest neighbors that were measured in 2002, or planned for field visits in 2004, 2005, and 2006, were selected to form five-plot clusters. The study was designed such that at least 30 five-plot clusters were available for sampling in each of the Four Corner States. The aerial image database will provide data in three ways: (1) each image taken over plots in the 2003 panel will provide a synoptic view (approximately 92 acres) of the vicinity of the FIA plot, enabling comparison of plot data with virtual plots of varying size (including whole image); (2) plots from other panels can be used as an ad hoc sample intensification of some geographic areas for 2003, enabling comparison of estimates based on different sampling intensities (table 2); and (3) time series up to 4 years in length, with one end of the series established by imagery and the other established by ground-based measurement, will be available for analysis on completion of the 2006 panel (table 2). The utility of data obtained in the third case will depend on the degree of agreement, in terms of variables such as stand density and mortality, that can be obtained between images and plots taken in the same year.

The FHP study, limited to Utah and Nevada, is focused on detailed identification and documentation of agents and the progression of mortality over time. Plot locations were stratified by ecoregion section (Cleland *et al.* 2004) in the two-State area, with at least 10 plots available for sampling in each of nine ecoregion sections. Under the FHP study plan, the selected plots will be visited every year for at least 5 years. Damaging agents and their effects are recorded in more detail than is currently being done during FIA plot visits; FIA currently records up to three damaging

Table 2.—*Matrix of annual and adjunct inventory schedules.*

Year measured <sup>b</sup>	Year assigned to plot for FIA annual inventory <sup>a</sup>				
	2002	2003	2004	2005	2006
2002	FIA				
2003	FHTET	FIA, FHTET	FHTET	FHTET	FHTET
2004	FHP	FHP	FIA, FHP	FHP	FHP
2005	FHP	FHP	FHP	FIA, FHP	FHP
2006	FHP	FHP	FHP	FHP	FIA, FHP

FIA = IWFA annual inventory; FHTET = FHTET aerial image acquisition; FHP = Region 4 FHP ground-based survey.

<sup>a</sup> Columns represent plots measured repeatedly over time.

<sup>b</sup> Rows represent intensification of the sample in a given measurement year—i.e., measurement of plots not scheduled for FIA annual inventory in that year.

agents and their severity, whereas the FHP study attempts to list all damaging agents present on the plot. Only FIA tree variables related to damage and mortality are recorded; variables such as height and diameter are not remeasured, in part because of low growth rates and to minimize impacts to the plot. The FHP study will also sample seedlings over a larger area than is measured in the FIA plot design, and seedling status will be followed over time. The FHP study will produce data in the following ways: (1) “expert” evaluation and a comprehensive listing of agents provides a database of damaging agents that can be compared to agents recorded by FIA crews; (2) a series of annual visits will allow comparison of agents present before, during, and after mortality occurs; and (3) as with the FHTET study, a local sample intensification and the creation of time series that can be used to supplement annual FIA panel data will occur (table 2).

## What the Data Show

Preliminary analysis of the FHTET and FHP studies is beyond the scope of this article, but data from FIA periodic and annual inventories offer some interesting insight into the progression of drought-related mortality across the Southwest and how annual panel data might be analyzed to improve the quality of mortality estimates. Annual data from Arizona, Colorado, and Utah are available for preliminary analysis. In addition, recent periodic inventories from Arizona, New Mexico, and Utah quantified predrought conditions of pinyon-juniper forests. For the sake of simplicity, the figures and trends presented here represent only

the pinyon component of the pinyon-juniper type. Although junipers and other species have suffered mortality in some areas, they are, to date, largely unaffected in the pinyon-juniper type.

The IWFIA program defines a mortality tree as one judged to have died within 5 years of the measurement date. For reporting purposes, measured mortality is converted to an annual figure. Periodic inventory data suggest that background mortality is relatively low for species that occur in the pinyon-juniper type (table 3). One possible explanation for low annual mortality may be the low growth rates that are typical of the type and stand dynamics that are somewhat different from other forest types. Following disturbance, pinyon and juniper species are more likely to gradually accumulate on the site as opposed to regenerating in large numbers and self-thinning over time. This process is most evident where the forest is encroaching on grasslands or sagebrush. This means that background mortality due to competition is less common in the pinyon-juniper type than, e.g., in ponderosa pine, which is listed in table 3 for comparison.

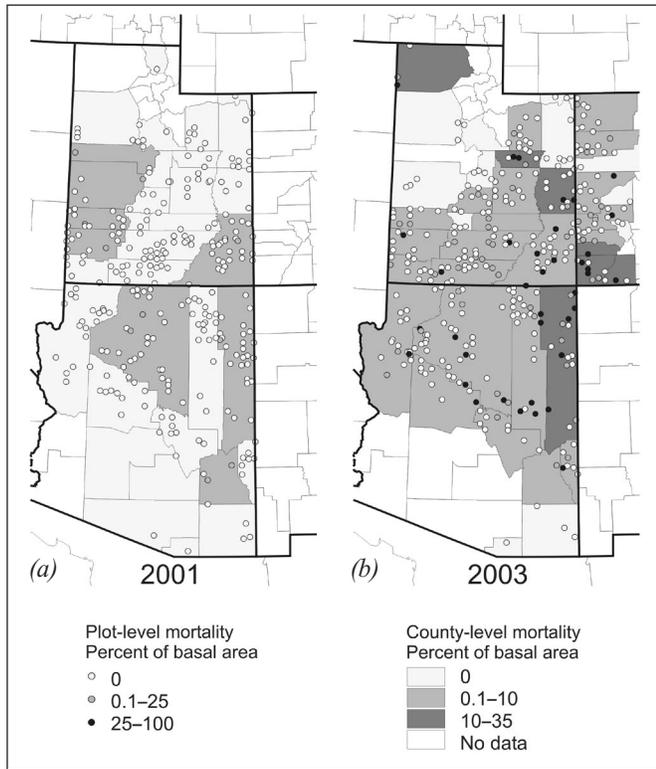
Annual inventory data show that drought-related mortality has occurred widely across the Southwest, although large numbers of plots remain unaffected (fig. 1). In the early stages of drought (2000–01), nearly all the mortality occurring at the county scale was located in one or two plots (fig. 1a). As the event progressed, mortality was recorded on many more plots, but considerable variation still existed within counties (fig. 1b). In the case of counties in which 10 or more plots were measured annually, however, mortality trends appear to be consistent with trends in adjacent counties also containing moderate numbers of plots.

Table 3.—Annual mortality for selected species based on most recent periodic inventory, by State.

Species	Mortality as a percent of volume <sup>a</sup>		
	Arizona (1999) (%)	New Mexico (2000) (%)	Utah (1995) (%)
Common pinyon	0.163	0.079	0.231
Singleleaf pinyon	—	—	0.145
Ponderosa pine	0.212	0.365	0.479
Alligator juniper	0.205	0.061	—
Oneseed juniper	0.011	0.009	—
Rocky Mountain juniper	0.003	0.082	0.047
Utah juniper	0.009	0.072	0.016

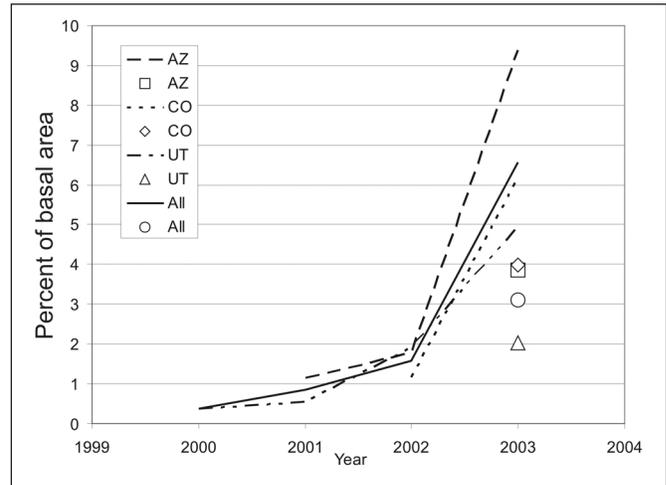
<sup>a</sup> Includes all causes of mortality, including fire. Mortality data are based on O’Brien (2002) for Arizona, O’Brien (2003) for New Mexico, and O’Brien (1999) for Utah.

Figure 1.—Plots in the pinyon-juniper type showing plot-level and county-level mortality of pinyon species.



When all plots are combined at State or regional scales, it is evident that the annual inventory has captured the rapid increase in drought-related mortality across the Southwest (fig. 2). Two aspects of figure 2 are worth noting. First, the trends shown by each statewide curve are similar, even though the record lengths are different. This lends to confidence in the results, even before confidence intervals have been computed. They also agree with anecdotal accounts of the progression of the event to date. Second, the point estimates created by combining all available panels give some indication as to the degree of lag bias that can occur in the event of rapid onset, accelerating changes. For example, the combined estimate for Utah is less than half that estimated by the 2003 data alone. In addition, estimates for different States cannot be combined using all available panels because of the differing record lengths. Note that the combined estimate for Arizona, which has just over 9 percent mortality according to the 2003 panel alone, is about equal to the combined estimate for Colorado, in which just over 6 percent of the basal area has died. This result is due to the fact that regional mortality was

Figure 2.—Mortality trends in Arizona, Colorado, and Utah. Lines are based on individual annual panels and symbols are based on combining all available panels within a State. Symbols are shown in 2003 for clarity, but each represents the midpoint of the record for each respective State.



low in 2001, the extra year in the Arizona record. This illustrates that regional combinations are limited to the lowest common denominator in terms of the number of concurrent panels in the area of interest.

## What Can Annual Inventory Tell Us?

Based on early results, the potential usefulness of annual panels as independent samples and time series data appears promising. Annual inventory appears able to detect trend and magnitude of short-term change during a widespread patchy event such as drought-related mortality. It also appears that relatively low levels of change can be detected, at least in cases where the variable of interest (in this case, background mortality) is typically at low levels and relatively constant over time and space. Status and trends can probably be estimated with a reasonable degree of confidence at larger scales. Some reduction in variance may be possible using strata that are not commonly used in FIA reporting, such as ecoregional units or discrete population segments. Drawing some conclusions at medium geographic scales, such as county or national forest, may be possible, but this ability is largely dependent on the distribution of the forest type of interest in the geographic area.

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For widespread, rapid onset phenomena such as drought-related mortality, combining panels may produce an unacceptable degree of lag bias. To produce results that accurately reflect current conditions and trends in the field, earlier panels must be brought forward using methods that account for rapid change, or annual panels must be used independently. In cases where panels are combined, the methodology must account for different lengths of time series that exist in different States.

The ongoing mortality event presents an opportunity to evaluate the efficacy of the FIA annual inventory system. The pinyon-juniper type was featured here; however, drought-related mortality has occurred to some degree in several other common forest types. Although the preliminary results look promising, acceptance of final results can only occur following the application of rigorous statistical evaluation. In addition, data obtained from adjunct studies such as those conducted by FHTET and FHP should be used to evaluate results based on FIA data alone.

## Acknowledgments

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## National Detection Surveys for Sudden Oak Death

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**Abstract.**—The Forest Health Monitoring program, a partnership of Federal and State forest management agencies, has developed and tested protocols for identifying and surveying forest ecosystems that may be vulnerable to invasion by *Phytophthora ramorum*, the cause of Sudden Oak Death in California and Oregon. This detection survey is targeting areas outside the currently known distribution of *P. ramorum*, including eastern oak forests. Sampling intensity is based on a risk map that identifies areas at high, moderate, and low risks of invasion. Pilot tests of the detection survey were conducted in seven States in 2003. In early 2004, regulatory officials discovered that nursery plants from

nurseries infested with *P. ramorum* were shipped throughout the United States. This discovery resulted in a major expansion and refocusing of detection surveys for *P. ramorum* during the spring of 2004. Surveys were conducted in 36 States with emphasis on forests near nurseries that received *P. ramorum*-infested plants. The cumulative number of locations surveyed during the 2 years now exceeds 1,100, with more than 5,600 samples submitted for laboratory analysis for *P. ramorum*. The pathogen was confirmed in only two locations in San Francisco County, CA. This survey indicates that *P. ramorum* is not widely established on native vegetation in the United States outside the known distribution in California and Oregon. Detection surveys will continue in 2005.

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## Sole: Online Analysis of Southern FIA Data

Michael P. Spinney, Paul C. Van Deusen, and Francis A. Roesch<sup>1</sup>

**Abstract.**—The Southern On Line Estimator (SOLE) is a flexible modular software program for analyzing U.S. Department of Agriculture Forest Service Forest Inventory and Analysis data. SOLE produces statistical tables, figures, maps, and portable document format reports based on user selected area and variables. SOLE's Java-based graphical user interface is easy to use, and its R-based analysis engine is fast and stable. Each of the program's components (data retrieval, statistical analysis, and output) can be modified individually. This adaptability encourages outside development of analysis algorithms.

### Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service has been collecting forest inventory data since 1930. Database structure and inventory design have evolved to accommodate available technology and satisfy user demand. The most recent version of the FIA Database (FIADB), available at [http://www.ncrs2.fs.fed.us/4801/FIADB/fiadb\\_documentation/FIADB\\_DOCUMENTATION.htm](http://www.ncrs2.fs.fed.us/4801/FIADB/fiadb_documentation/FIADB_DOCUMENTATION.htm), includes new ecological variables and older variables with modified definitions. The size of the FIADB can be intimidating to some users, and the database structure can confuse others. Readily accessible, easy-to-use tools are necessary to ensure proper analysis of FIA data.

FIA data are analyzed periodically by the USDA Forest Service and published as a standard suite of tables for a State or region. FIA has recently converted from a periodic to an annual inventory system and now publishes reports every 5 years. This schedule

may not be satisfactory for users who require more up-to-date reports or who are interested in information for areas other than States or regions. Production of customized reports requires users to download data, replicate the relational database, and then correctly query and summarize the data. Not all users with special data needs are willing to invest this amount of effort.

Web-based FIA analysis tools simplify the production of customized reports by eliminating the need to understand the underlying database structure. FIA's MapMaker (<http://www.ncrs2.fs.fed.us/4801/fiadb/fim17/wcfim17.asp>) is the USDA Forest Service's official Web-based analysis tool that uses standardized FIA analysis algorithms. Another online tool, the Southern On Line Estimator (SOLE; <http://ncasi.uml.edu/SOLE>) has been developed cooperatively by the USDA Forest Service and the National Council for Air and Stream Improvement. SOLE, a Web-based tool for analyzing annual FIA data, has a Java-based graphical user interface and an R-based analysis engine that employs both standardized FIA and alternative algorithms.

### Sole Structure Overview

Flexibility has been the top priority during the development of SOLE's structure. Each of the three main components of the program (data retrieval, statistical analysis, and output) was developed to be independently modifiable, which facilitates outside development of analysis algorithms.

The user completes a query by sequentially selecting tabs at the top of the user interface. After choosing States in the **State Selection** window, the user progresses through the **SOLE Map, Variable Selection, Filters** (optional), **Analysis**, and/or **Mapping** tabs. The application progresses automatically as the user completes requirements associated with each tab. Detailed instructions can be found in the help files linked to each tab.

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## Using the Program

### State Selection

The application begins with the **State Selection** window. States for which annual data are available have black backgrounds, and States for which only periodic data are available are “grayed out” (i.e., unavailable for analysis). When a State is selected, its name is listed, and the State is highlighted with green. When done selecting States, the user clicks the orange bar at the bottom of the window to proceed to the **SOLE Map** tab, where individual counties may be selected (fig. 1).

### SOLE Map

Individual counties can be chosen with the **Select by County** button, or all counties in the State can be chosen with the **Select All Counties** button. Clicking on the **Retrieve Data** button loads the necessary data files into the statistical program, R (R Development Core Team 2003). After the data files have been loaded, the next group of tabs, **Variable Selection** and **Filters**, become available (fig. 2).

### Variable Selection

Currently, only FIADB volume variables are available for analysis. These are grouped in 2 ways: Quantitative (continuous data, i.e., any volume or biomass estimate), and Qualitative (categorical data, such as productivity class). In addition, Quantitative Variables are grouped based on diameter greater or less than 5 inches. The diameter breakdown preserves the precision of volume estimates by ensuring that no data for trees less than 5 inches diameter at breast height are included in merchantable volume estimates (fig. 2). All analyses require selection of one Quantitative and at least one Qualitative Variable.

### Filters

All data for the area of interest are analyzed unless analysis is restricted by an optional filter. The filters currently offered include stand size, stand origin, all live stocking, growing-stock stocking, specific forest type, site productivity class, physiographic class, ownership group, owner, reserved class, and measurement year. Users can customize their analyses by specifying particular levels of filters. Filter status is displayed at the top of each analysis.

Figure 1.—SOLE map selection tab, for county selection and data retrieval.

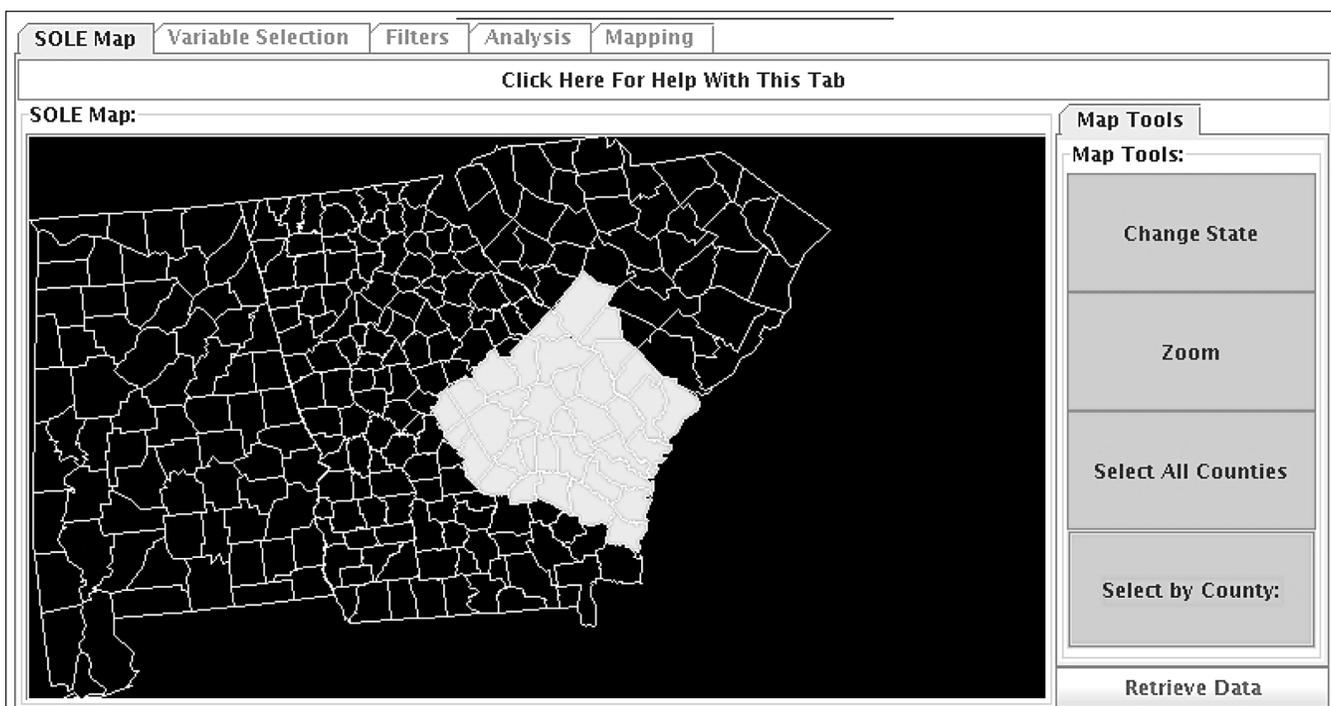
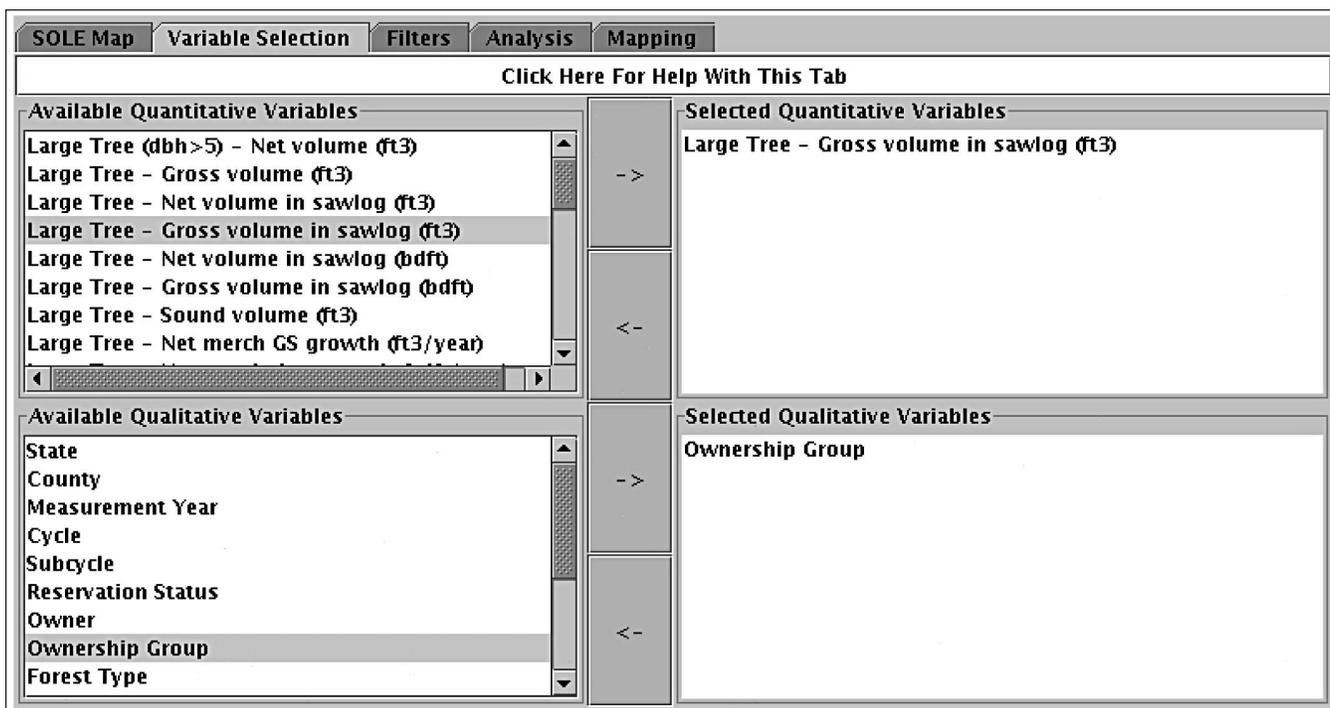


Figure 2.—SOLE variable selection tab.



### Analysis

Charts and tabular analyses are launched from the **Analysis** tab, as illustrated in fig. 3. The header of each analysis indicates which filters, analysis, and variables have been selected.

**Tabular Analysis.**—SOLE can now calculate the means on which the population summary statistics are based by either a moving average (MA) or a mixed estimator (ME) method (Van Deusen 2001). The MA estimator, the default estimator for FIA analysis, provides a complete estimate for a specific 5-year period. MA analysis results in the following seven tables:

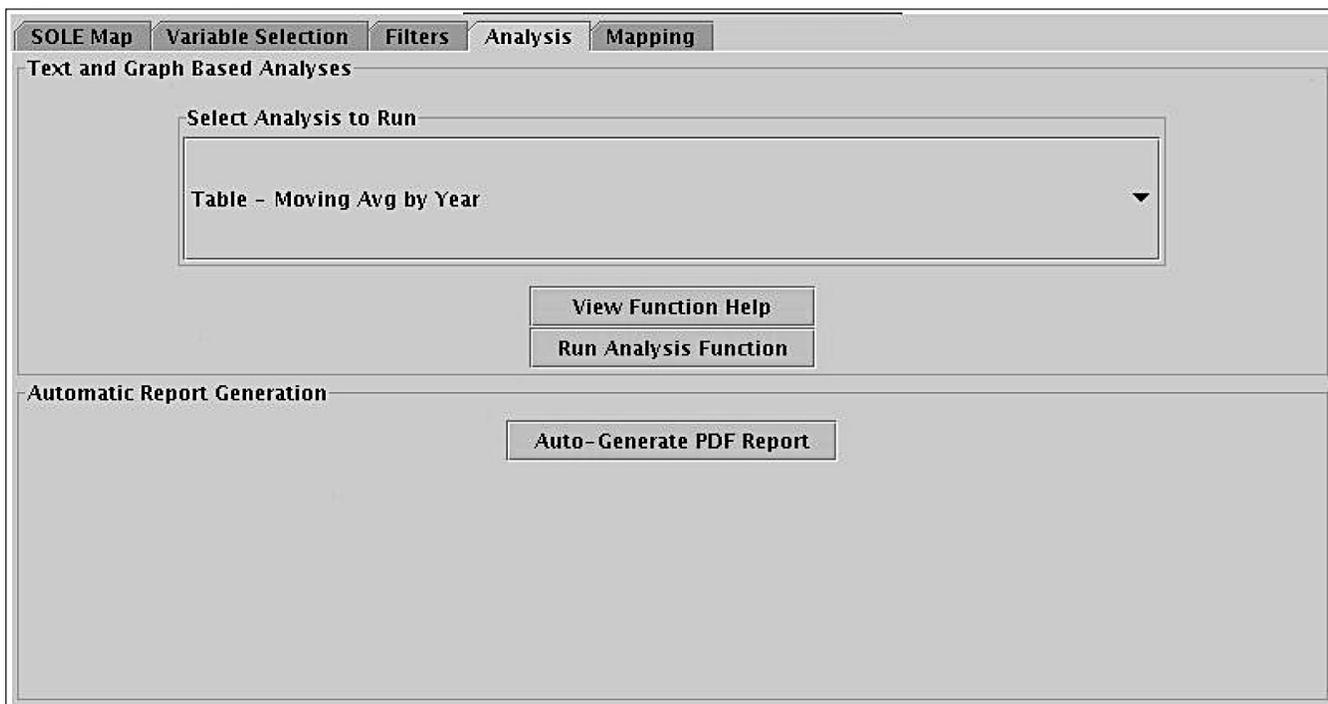
1. MA (Quantitative Variable of interest per acre).
2. Standard error of each element of table 1.
3. Sampled area (acres) represented by the plots used in the calculation of table 1 (summarizes the FIADB variable EXPCURR).
4. Estimated population total for the Quantitative Variable of interest (equals MA multiplied by area).
5. Standard error of the total estimate.
6. Total number of plots used in calculation, by each level of the Qualitative Variable.
7. Number of plots by measurement year.

ME analysis results in the following six tables that have measurement years as columns:

1. ME mean Quantitative Variable of interest by year (per acre).
2. Standard error per year.
3. Sampled area (acres) represented by the plots used in the calculation of table 1.
4. Estimated population total for the Quantitative Variable of interest.
5. Standard error for the total estimate.
6. Adjusted sample size by measurement year.

The MA provides a complete estimate for each specific 5-year period. When the MA is used, change can be determined after a second MA can be calculated in year 6. In this case, the panel 1 data that are measured in year 1 are dropped from the estimator, and the panel 1 data measured in year 6 are added. Note that 80 percent of the data are common to the two consecutive MA estimates. Both the MA and ME can provide full-data change estimates, but to which specific years the MA difference estimator should be applied is not obvious. Another reason the ME estimator might be preferred is its ability to model explicit

Figure 3.—SOLE analysis selection tab.



trends, which permits the use of all available plots to estimate rates of change for any point in time covered by the panel series.

**Graphical Analysis.**—Graphs are often the most comprehensible means of presenting data characteristics. SOLE offers bar charts, box plots, pie charts, and XY plots. Bar and pie charts show a basic distribution of the Quantitative Variable by each level of the Qualitative Variable. XY plots offer some insight into the data distribution and frequency based on the number and distribution of points with respect to the axes. Box plots convey the most statistical information about the data because they show the mean, interquartile range, and outliers for each level of the Qualitative Variable.

**Map Analysis.**—County-level maps can be created from the **Mapping** tab. Basic maps of the mean and median are supplemented by more complex ratio maps, which display the ratio of filtered to unfiltered data. For example, the user can filter for a specific ownership group and then view a map of the proportion of volume on land owned by that group to the volume on all land owned by all groups.

**Portable Document Format Report.**—At the simplest level, the portable document format (more commonly known as PDF) report could be completely contained such that the user selects an area of interest and then generates a report containing a pre-determined combination of text and tabular, graphical, or map analyses describing forest attributes for that area. Potentially, this feature could be developed to produce an array of standard FIA report tables at the click of a button, giving the user the ability to produce current reports at each FIADB update.

## Summary

Web-based FIA analysis tools are essential for proper analysis of FIA data. SOLE provides a simple interface that allows users to obtain customized analytical results. SOLE is constructed in a modular fashion that makes it easy to add new capabilities. SOLE provides a wide range of options for users who want to analyze FIA annual inventory data and obtain graphical and tabular results. Flexibility in each component of SOLE ensures that SOLE remains highly adaptable to changes in database structure and user needs.

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## Acknowledgments

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## Practical Considerations When Using Perturbed Forest Inventory Plot Locations To Develop Spatial Models: A Case Study

John W. Coulston<sup>1</sup>, Gregory A. Reams<sup>2</sup>, Ronald E. McRoberts<sup>3</sup>, and William D. Smith<sup>4</sup>

**Abstract.**—U.S. Department of Agriculture Forest Service Forest Inventory and Analysis plot information is used in many capacities including timber inventories, forest health assessments, and environmental risk analyses. With few exceptions, actual plot locations cannot be revealed to the general public. The public does, however, have access to perturbed plot coordinates. The influence of perturbed plot coordinates on the development of spatial models is unknown. We examined the influence by comparing the accuracies of two spatial models for predicting forest biomass, ordinary kriging and residual kriging. We developed each model using the actual coordinates and 10 independent perturbations of the actual coordinates. We tested for differences in accuracy using analysis of variance. No statistically significant difference in accuracy was found. The results represent only a small portion of the possible outcomes, however. We suggest a simulation study to examine the spatial range of influence that plot coordinate perturbation has on model accuracy.

### Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service collects data on tree and forest attributes using a quasi-systematic sample. These data are used for many purposes including timber inventories, forest health assessments, and risk assessments. Because of privacy issues, actual plot locations cannot be revealed to

scientists outside the FIA program or the general public. FIA has implemented several methods for perturbing plot locations to protect plot integrity and ensure landowner privacy. Although the perturbed plot locations are available to the public, the effects of the perturbations on the accuracy of spatial models are unknown.

Before 2002, FIA field plot locations perturbed within 1.6 km of the actual locations were available to the general public. Although currently no national standard exists for perturbing plot coordinates, guidelines that may be satisfied at the regional level using different techniques are available. One method currently used is to randomly shift plot locations and swap data among plots. In this article, we use the term “perturbed” to denote both the random shift in plot location and the swapping of plot attributes. Plot perturbation influences the spatial characteristics of the data and, therefore, can influence the accuracy of spatial models.

Spatial models and FIA data are widely used in environmental assessments. For example, Morin *et al.* (2003) used FIA field plot data, perturbed plot locations, and median indicator kriging to interpolate a surface of percent forest basal area of species susceptible to *Phytophthora ramorum* (a fungus-like organism that causes Sudden Oak Death). This interpolated surface was then intersected with other spatial data and used to assess the potential susceptibility of Eastern forests to *Phytophthora ramorum*. Coulston *et al.* (2003) used ordinary kriging to predict potential ozone injury at FIA phase 3 (formerly forest health monitoring) plot locations and assess ozone injury risk to ozone-sensitive Northeastern tree species. This analysis was conducted using the centers of the sampling hexagons (White *et al.* 1992) as plot locations rather than the actual plot locations.

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Spatial models generally rely on the relationship among observations by distance and direction (e.g., kriging). More complicated spatial models may further rely on ancillary data that are intersected with plot data (e.g., residual kriging). The objective of this study was to examine the influence of FIA plot coordinate perturbations on the accuracy of two spatial models for predicting forest biomass. The first model was ordinary kriging of forest biomass, and the second model was residual kriging in which forest biomass was predicted using percent forest and leaf area index (LAI) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data.

## Methods

Plot-level estimates of percent forest land use and forest biomass were obtained for 3,914 FIA plots in Minnesota. The plot locations were randomly perturbed 10 different times in accordance with the procedures used by the FIA program of the North Central Research Station, USDA Forest Service. Perturbing plot locations entails randomly shifting the x and y coordinates of the actual locations for all plots, and swapping plot attributes (e.g., tree volume  $m^3ha^{-1}$ ) entails exchanging coordinates among a proportion of plots. These manipulations are usually done within a county, and plot attributes can be swapped only if the plots are sufficiently similar (e.g., same forest type). The data set consisting of the percent forest land use and forest biomass estimates and the actual plot locations is denoted REAL, while the 10 data sets consisting of the estimates and the perturbed plot locations are denoted REPS. Before the spatial models were developed, we randomly extracted 180 plots (approximately 5 percent) from the data set. Average plot biomass for these extracted plots was 26.6 tons/acre, and the standard deviation was 19.3 tons/acre. The biomass models were then developed without these plots, model predictions were made for the 180 plots, and the accuracy of the models with and without plot coordinate perturbations (i.e., for the REAL and REPS data sets) was compared.

Because ordinary kriging is a central technique in this analysis, we provide a brief overview. (For more details, see Cressie 1993 or Isaaks and Srivastava 1989.) Ordinary kriging is a standard interpolation technique with a minimum of three steps required

to estimate values at unmeasured locations. First, the empirical semivariogram is calculated; second, the empirical semivariogram is modeled; and third, parameter estimates obtained from the modeled semivariogram are used to predict values at unmeasured locations. The semivariance between values for a particular lag distance  $h$  is

$$\gamma(h) = \frac{1}{2N(h)} \sum (v_j - v_i)^2$$

where  $N$  is the number of pairs  $(i,j)$ , and  $v_i - v_j$  is the difference between the values of pair  $(i,j)$ . A semivariogram is a graph of semivariance by distance class. Several model types may be used to model the empirical semivariogram, including the Gaussian model, wave model, power model, and exponential model. Most variogram models can be characterized by three parameters: the nugget, sill, and range. The nugget refers to the y-intercept of the modeled semivariogram and is a function of microscale variation or measurement error. The sill refers to the maximum value of semivariance (i.e., the total variation in the data), and the range is the distance at which the semivariance reaches 95 percent of the sill.

After the semivariogram has been modeled, ordinary kriging can be used to estimate values at unsampled points. Ordinary kriging is a weighted average such that

$$\hat{V}_0 = \sum_{i=1}^n w_i V_i$$

where  $\hat{V}_0$  is the estimate at unmeasured location 0,  $w_i$  is the weight for the  $i^{\text{th}}$  observation, and  $V_i$  is the value of the  $i^{\text{th}}$  observation. The weights sum to 1 and are determined by minimizing the overall estimation error. The estimation variance is

$$S_0^2 = w_i \gamma(s_i - s_0) + \lambda$$

where  $\gamma(s_i - s_0)$  is the modeled semivariance for the distance between  $s_i$  and  $s_0$ , and  $\lambda$  is the Lagrange multiplier from solving the linear system of equations for minimum estimation error.

We predicted forest biomass using kriging at each of the extracted 180 plots using the REAL and REPS data sets. To accomplish this, we first examined the sample variograms for

each of the 11 data sets. Second, we modeled the sample variograms with the power model

$$\gamma(h) = C_1(h)^a$$

In this model,  $a$  is dimensionless and dictates the shape of the variogram, and  $C_1$  has the same dimension as the variance. The parameters  $C_1$  and  $a$  were estimated using weighted nonlinear regression where the weight was inversely proportional to distance and semivariance. The logic behind this weighting was that small semivariance values near distance 0 have the most importance for kriging. This weighting is similar to the weighting proposed by Cressie (1985). Third, we used the ordinary kriging equation to predict biomass values at the 180 locations extracted before model development using the REAL and REPS data sets.

Delhomme (1978, 1979) first proposed combining regression and kriging. In our study, we used residual kriging for which a regression model was developed to predict forest biomass using percent forest and LAI. The model residuals were then kriged. The percent forest values were collected in the field for each plot, and the LAI values were obtained by intersecting a 1-km resolution map of LAI with the REAL and REPS data sets. The model was developed empirically with general form

$$E(Bm) = \exp(cP_f + g\sqrt{P_fLAI}), \quad (1)$$

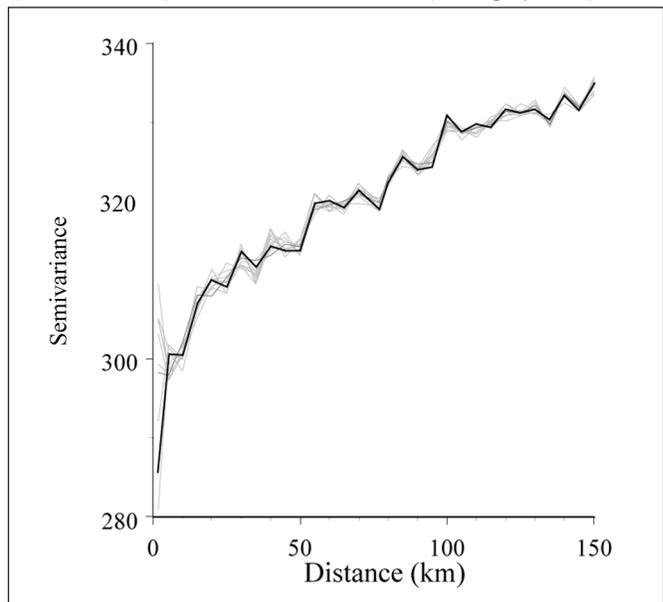
where  $E(Bm)$  is the statistical expectation of forest biomass (tons/acre),  $\exp(\cdot)$  is the exponential function,  $P_f$  = percent forest land use,  $c$  = percent forest parameter, LAI = leaf area index derived from MODIS satellite imagery, and  $g$  = parameter for adjusted LAI. To solve model (1), we first transformed it into its linear form by taking the natural logarithm of each side. Next, we used ordinary least-squares to estimate each parameter. The linear model was then back-transformed, and the semivariance of the residuals was examined and modeled with the power variogram model. We then used ordinary kriging to predict the residual for the prediction for each of the 180 plots extracted from the analysis. The final predicted value of forest biomass was the sum of the predicted value from model (1) and the predicted residual from kriging. This method was applied to the REAL and REPS data sets.

We used analysis of variance to examine the influence that plot coordinate perturbation had on the accuracy of the spatial models. Specifically, we tested for differences in mean error and mean squared error among results for the 180 plots extracted from the data. If we observed an overall difference, we then examined the reason for the observed difference using Tukey's studentized range test.

## Results

We visually inspected the empirical variograms of forest biomass for differences. Plot coordinate perturbation had the greatest influence on semivariance values between plots closer than approximately 1,900 m (fig. 1); i.e., the plot coordinate perturbation changed correlations among observations for plots separated by relatively short distances. The total variation and range of spatial autocorrelation were relatively uninfluenced which was expected because relatively small shifts in plot locations should influence only local variability. We used a power variogram model to develop the theoretical variogram. The power model does not technically have a sill and range, but the plot coordinate perturbation did influence the parameter estimates  $\hat{C}_1$  and  $\hat{a}$ .

Figure 1.—Empirical semivariogram for the REAL data set (solid dark line) and the REPS data sets (solid gray lines).



No statistically significant difference exists in mean error or mean square error among kriging estimates based on the REAL and REPS data sets (table 1). The mean error of estimates based on the REAL data set was 1.192 tons/acre, which fell between the high and low limits from the REPS data sets. The estimates based on the REAL data set had the highest mean square error. Because no statistically significant difference exists between estimates based on the REAL and REPS data sets, they all fell in the same Tukey grouping.

We developed a regression model to predict forest biomass based on percent forest and LAI. The linearized model had  $R^2 = 0.88$ ,  $\hat{c} = 2.59$ , and  $\hat{g} = 0.23$ . Standardized regression coefficients were used to compare the influence of each predictor variable when the variables are measured in different units (SAS 1999). The standardized regression coefficients were  $\hat{c} = 0.811$  and  $\hat{g} = 0.127$ , suggesting that the model was most heavily influenced by  $P_f$ . Figure 2 shows the nonlinear form of model (1). The parameter estimates were slightly different for models developed from the REPS data sets. The range of estimates for the  $c$  parameter was 2.59–2.73, and the range of estimates for the  $g$  parameter was 0.16–0.23. All the regression models based on the REPS data sets had  $R^2 \approx 0.88$  which was similar to that obtained for the regression model based on the REAL coordinates.

No statistically significant difference exists in mean error or mean square error among residual kriging estimates based on

the REAL and REPS data sets (table 1). Residual kriging using the REAL data set had a mean error of 1.201 tons/acre and a mean squared error of 316.83 (tons/acre)<sup>2</sup>. The highest mean error from the REPS data sets was 1.308 tons/acre, and the highest mean squared error was 321.12 (tons/acre)<sup>2</sup>. The lowest mean error and mean squared error were 1.032 tons/acre and 311.36 (tons/acre)<sup>2</sup>, respectively. Because no statistically significant difference exists between estimates based on the REAL and REPS data sets, they all fell in the same Tukey grouping.

Figure 2.—Predicted biomass based on model (1).

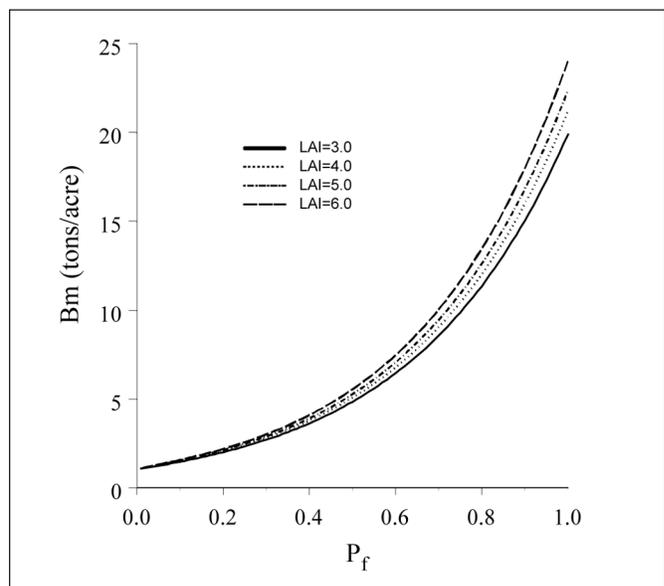


Table 1.—Mean prediction error and mean squared prediction error for estimates of biomass based on the REAL and REPS data sets.

Data	Kriging estimates	Residual kriging estimates	Mean error	Mean squared error
	Mean error	Mean squared error		
	<i>tons/acre</i>	<i>(tons/acre)<sup>2</sup></i>	<i>tons/acre</i>	<i>(tons/acre)<sup>2</sup></i>
REAL	1.192	343.07	1.201	316.83
REPS01	1.211	339.24	1.032	315.43
REPS02	1.218	339.13	1.247	321.12
REPS03	1.184	338.40	1.212	213.97
REPS04	1.190	340.29	1.221	316.48
REPS05	1.234	339.07	1.308	315.61
REPS06	1.179	341.23	1.083	315.07
REPS07	1.213	338.27	1.174	316.12
REPS08	1.159	338.40	1.123	316.04
REPS09	1.203	341.68	1.189	316.85
REPS10	1.177	338.73	1.281	311.36

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## Discussion

In this study, the plot coordinate perturbations did not influence the accuracy of the spatial models. Two characteristics of the data, however, may have contributed to this outcome. First, the biomass variable had a weak spatial structure based on the variogram. Second, the regression model was based on percent forest estimates from the field and LAI estimates based on MODIS imagery. Based on the standardized regression coefficients, the percent forest variable had the highest weight in the model.

We considered forest biomass to exhibit a weak spatial structure because the proportion of the semivariance explained by distance was relatively small. We can examine the strength of the spatial structure in many ways. With the power variogram model, the  $C_1$  parameter typically has estimates between 0 and 2 (SAS 1996). When  $C_1$  approaches 0, the semivariogram approaches a horizontal line. Our estimate was  $\hat{C}_1 = 0.033$ , which suggests a weak spatial structure; i.e., biomass has large variance and exhibits little spatial correlation, even at small distances. When the empirical semivariogram exhibits a horizontal linear structure (i.e., slope = 0 or horizontal line), the best linear unbiased predictor is the average. When the spatial structure is weak, the kriging equation will produce estimates close to the global average. We hypothesize that when the variable of interest has a weak spatial structure, the plot coordinate perturbations have a minimal effect on the accuracy of kriging estimates because estimates approach the global average.

The regression model developed for this study was most heavily influenced by the percent forest variable. This variable was collected in the field so that each plot, regardless of plot coordinate perturbation, had the actual field estimate for percent forest. The LAI variable was obtained by intersecting the imagery with the plot locations. The MODIS data were 1-km in resolution which matched well with the plot coordinate perturbation, because 95 percent of the perturbed plot locations were within 0.8 km of the actual plot location. Also, LAI estimates were adjusted by the percent forest in model (1). We suggest that the influence of plot coordinate perturbation on the accuracy of residual kriging depends on the resolution and the spatial autocorrelation of the intersected information.

For spatial models developed by intersecting ancillary data (e.g., regression kriging, residual kriging, mixed models), the two most important characteristics of the ancillary data are the resolution and the spatial autocorrelation. The resolution of the ancillary data is important because the probability that a plot will be assigned incorrect information during intersection decreases with decreasing resolution. For example, plots will more likely be assigned the correct value from intersection when the resolution of the ancillary data is 5 km as opposed to 30 m. The autocorrelation of the ancillary data is also important because plots will more likely be assigned a value similar to the correct value when high autocorrelation exists. For example, if the resolution of the ancillary data is 30 m, and the spatial autocorrelation is zero (i.e., a random spatial pattern), the probability of assigning the correct value to the plot is very low. If the resolution of the ancillary data is 30 m, and the spatial autocorrelation is large, however, the probability of assigning the correct value to the plot is much greater.

## Conclusions

The objective of this study was to examine the influence of plot coordinate perturbation on the accuracy of kriging estimates and residual kriging estimates. For the cases we examined, no statistically significant influence on accuracy exists. Generalizations should be made with caution due to the potential influence of the following factors:

1. **Spatial structure in the variable of interest.** A weak spatial structure should produce little effect, while a strong spatial structure may produce a larger effect.
2. **Spatial resolution of ancillary data.** Coarse spatial resolution decreases the probability of assigning incorrect ancillary data values to a plot, while fine spatial resolution increases the probability.
3. **Spatial autocorrelation of ancillary data.** High spatial autocorrelation in ancillary data decreases the probability of large errors in the assignment of ancillary data value to a plot, while low spatial autocorrelation increases the probability.

We suggest that these topics be further investigated using simulated variables of known spatial structure.

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## A Model-Based Approach to Inventory Stratification

Ronald E. McRoberts<sup>1</sup>

**Abstract.**—Forest inventory programs report estimates of forest variables for areas of interest ranging in size from municipalities to counties to States and Provinces. Classified satellite imagery has been shown to be an effective source of ancillary data that, when used with stratified estimation techniques, contributes to increased precision with little corresponding increase in costs. A new approach to stratification based on using satellite imagery and a logistic regression model to predict proportion forest area is proposed. The results suggest that precision may be substantially increased for estimates of proportion forest area and volume per unit area.

### Introduction

The Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service reports estimates of forest variables for medium to large geographic areas of interest (AOI) such as counties, national forests, and States based on data collected from arrays of field plots. Due to budgetary constraints and natural variability among plots, sufficient numbers of plots frequently cannot be measured to satisfy precision guidelines for the estimates of many variables unless the estimation process is enhanced using ancillary data. Classified satellite imagery has been accepted as a source of ancillary data that can be used with stratified estimation techniques to increase the precision of estimates with little corresponding increase in costs (Hansen and Wendt 2000, McRoberts *et al.* 2002, Hoppus and Lister 2003). The objective of the study was to evaluate the utility of satellite image-based stratifications derived from logistic regression predictions of proportion forest area (P) for increasing the precision of estimates of volume per unit area (V) and P.

### Data

The FIA program has established field plot locations using a sampling design that is assumed to produce a random, equal probability sample (McRoberts and Hansen 1999). The sampling design is based on a tessellation of the United States into approximate 2,400-ha hexagons derived using the Ecological Mapping and Assessment Program methodology (White *et al.* 1992). At least one permanent plot has been established in each hexagon. The hexagonal array has been divided into five nonoverlapping, interpenetrating panels, and measurement of plots in one panel is completed before measurement of plots in the next panel is initiated. Panels are targeted for selection on a 5-, 7-, or 10-year rotating basis, depending on the region of the country.

In general, locations of forested or previously forested plots are determined using Global Positioning System receivers, while locations of nonforested plots are determined using aerial imagery and digitization methods. Each field plot consists of four 7.31-m (24-ft) radius circular subplots. The subplots are configured as a central subplot and three peripheral subplots with centers located at 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Among the observations field crews obtain are the proportions of subplot areas that satisfy specific ground land use conditions. Subplot estimates of P are obtained by collapsing ground land use conditions into forest and nonforest classes consistent with the FIA definition of forest land. Field crews also measure the diameter at breast height (d.b.h.), 1.37 m (4.5 ft) and the height of each tree with d.b.h. ≥ 12.5 cm (5 in). Statistical models are used to predict the volume of each tree from the d.b.h. and height measurements, and volumes of all trees with d.b.h. ≥ 12.5 cm on each subplot are added to obtain subplot estimates of V. The national FIA program uses an infinite sampling framework and attributes aggregations of data for the four subplots to the point

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corresponding to the center of the central subplot. For two study areas (fig. 1), one in southern Indiana and one in northern Minnesota, FIA plot data and three dates of Landsat Thematic Mapper (TM) or Enhanced TM+ imagery were used. Observations of P and V obtained between 1999 and 2003 were available for 1,211 FIA plots in the Indiana study area and for 2,114 FIA plots in the Minnesota study area.

Landsat imagery for one Indiana scene (path 21, row 33) and one Minnesota scene (path 27, row 27) was obtained from the Multi-Resolution Land Characterization 2001 land cover mapping project (Homer *et al.* 2004) of the U.S. Geological Survey. Imagery for three dates corresponding to early, peak, and late vegetation green-up (Yang *et al.* 2001) were obtained for each scene: April 2001, July 2000, and October 2001 for the Indiana scene and March 2000, July 1999, and October 1999 for the Minnesota scene. Preliminary analyses indicated that Normalized Difference Vegetation Index (NDVI) (Rouse *et al.* 1973) and the tasseled cap (TC) transformations (brightness, greenness, and wetness) (Kauth and Thomas 1976, Crist and Cicone 1984) were superior to both the spectral band data and principal component transformations in predicting P. Thus, 12 satellite image-based predictor variables were used: NDVI and the three TC transformations for each of the three image dates. Because plots would eventually be assigned to strata derived from pixel classifications or predictions, the constraint that a plot could not sample multiple strata had to be accommodated, and the FIA plot configuration requires a 3 x 3 block of pixels for geospatial coverage, the mean of each transformation of the spectral values was calculated for each 3 x 3 block of pixels

and attributed to the center pixel of each block. Similarly, the FIA plot observations of P and V were attributed to the pixel containing the plot center.

## Methods

### Stratified Estimation

Stratified estimation requires accomplishment of two tasks: (1) calculation of the relative proportion of the land area corresponding to each stratum, and (2) assignment of each plot to a single stratum. After the classifications or predictions for the satellite imagery have been obtained and aggregated into useful strata, the two required tasks are relatively easy to accomplish. The first task is accomplished by counting the number of pixels in each stratum and then calculating the relative proportions of pixels in strata. The second task is accomplished by assigning plots to strata on the basis of the stratum assignments of their associated pixels.

Stratified estimates for FIA variables are calculated using standard methods (Cochran 1977):

$$\bar{Y}_{\text{Str}} = \sum_{h=1}^H w_h \bar{Y}_h, \quad (1)$$

and

$$\text{Var}(\bar{Y}_{\text{Str}}) = \sum_{h=1}^H w_j^2 \frac{\hat{\sigma}_j^2}{n_j}, \quad (2)$$

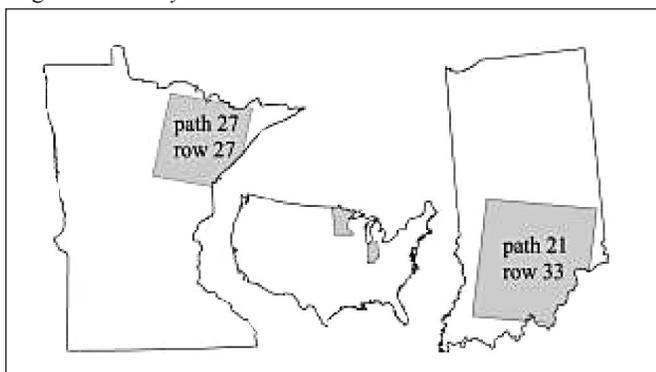
where

$$\bar{Y}_h = \frac{1}{n_h} \sum_{i=1}^{n_h} Y_{hi}, \quad (3)$$

$$\hat{\sigma}_h^2 = \frac{1}{n_h - 1} \sum_{i=1}^{n_h} (Y_{hi} - \bar{Y}_h)^2, \quad (4)$$

and where  $Y_{hi}$  is the  $i^{\text{th}}$  observation in the  $h^{\text{th}}$  stratum of the variable of interest;  $h=1, \dots, H$  denotes strata;  $w_h$  is the weight for the  $h^{\text{th}}$  stratum, calculated as the proportion of pixels in the AOI assigned to the stratum;  $n_h$  is the number of plots assigned to the  $h^{\text{th}}$  stratum;  $\bar{Y}_h$  is the sample mean for the  $h^{\text{th}}$  stratum; and  $\hat{\sigma}_h^2$  is the sample estimate for the stratum variance.

Figure 1.—Study areas.



The FIA program uses stratified estimation but not stratified sampling. For estimation purposes, at least five plots per stratum are considered necessary to obtain reliable stratified estimates. If fewer than five plots are assigned to a stratum, the user has four options: (1) combine similar strata, (2) increase the size of the AOI so that the stratum includes a sufficient number of plots, (3) combine strata and increase the size of the AOI, or (4) do not use stratified estimation.

The effectiveness of a stratification is often evaluated using relative efficiency (RE) calculated as follows:

$$RE = \frac{\text{V}\hat{\text{a}}\text{r}(\bar{Y}_{\text{SRS}})}{\text{V}\hat{\text{a}}\text{r}(\bar{Y}_{\text{Str}})}, \quad (5)$$

where  $\text{V}\hat{\text{a}}\text{r}(\cdot)$  is estimated variance,  $\bar{Y}_{\text{SRS}}$  is the estimate of the mean obtained under the assumption of simple random sampling (SRS), and  $\bar{Y}_{\text{Str}}$  is the estimate of the mean obtained using stratified estimation.  $RE > 1.0$  indicates that the strata and stratified estimation have the desired effect of reducing variance and increasing precision, while  $RE \approx 1.0$  indicates the strata are having little benefit.

### Model Prediction

Predictions of P for individual pixels in each study area were obtained using a logistic regression model (LOG):

$$E(\text{P}) = \frac{1}{1 + \exp(\beta_0 + \beta_1 X_1 + \dots + \beta_{12} X_{12})} \quad (6)$$

where  $E(\cdot)$  is statistical expectation,  $\exp(\cdot)$  is the exponential function, the  $\beta$ s are parameters to be estimated, and the Xs are the 12 transformations of the satellite image spectral values. Separate sets of parameter estimates were obtained for each study area.

Because the estimates of all parameters of model (6) are obtained from observations for all plots in the study area, the model prediction for each image pixel will also be based on the observations for all plots in the study area. Thus, because the same plots are assigned to strata as were used to calibrate the model from whose predictions the strata were derived, concern that the plots do not constitute random samples of strata may exist.

Breidt and Opsomer (2002) showed that for samples smaller than those used for model calibration for this study, this concern may be dismissed.

### Analyses

For each study area, the pixel predictions of P were grouped into 0.01-wide classes beginning with  $\hat{\text{P}} = 0.01$  and ending with  $\hat{\text{P}} = 1.00$ . Plots were assigned to the resulting 101 classes on the basis of the class assignments of the pixels containing the plot centers. The optimal grouping of the 101 classes into four strata was determined, subject to the constraint that no stratum with fewer than five plots was permitted. Within each study area, three optimality criteria were considered:  $RE_p$ ,  $RE_v$ , and  $RE_p + RE_v$ .

As a basis for comparison, means and standard errors for P and V were obtained for each study area under the SRS assumption. In addition, means, standard errors,  $RE_p$ , and  $RE_v$  were obtained for the approach to stratification used by the regional FIA program of the North Central Research Station (NC), USDA Forest Service. With the NC approach, four strata are derived from the 21 classes of the National Land Cover Data (NLCD) (Vogelmann *et al.* 2001, Homer *et al.* 2004). First, the NLCD classes are aggregated into forest and nonforest classes, and second, 2-pixel-wide forest edge and nonforest edge classes are constructed along the forest/nonforest boundary (Hansen and Wendt 2000, McRoberts *et al.* 2002). These four classes—Forest, Forest Edge, Nonforest Edge, and Nonforest—are then used as strata. For the Indiana study area, the four strata were derived from the 1992 version of the NLCD, while for the Minnesota study area, the four strata were derived from the 2001 version of the NLCD.

### Results

Estimates of mean P and V were nearly indistinguishable for the different approaches to stratification (table 1). In all cases,  $RE_p > RE_v$ , which is consistent with previous findings and can be attributed to the closer relationship between P and a forest/nonforest classification than between V and the classification. For both study areas, the LOG approach was superior to the

Table 1.—Comparisons of results of stratifications.

Approach	Strata optimization criterion	Indiana study area			Minnesota study area		
		Mean	SE	RE	Mean	SE	RE
Proportion forest area							
SRS		0.3383	0.0127	1.00	0.7279	0.0091	1.00
NC		0.3545	0.0067	3.60	0.7267	0.0073	1.53
LOG	RE <sub>A</sub>	0.3373	0.0052	5.87	0.7298	0.0060	2.33
LOG	RE <sub>V</sub>	0.3349	0.0060	4.50	0.7241	0.0064	1.74
LOG	RE <sub>A</sub> + RE <sub>V</sub>	0.3393	0.0053	5.72	0.7298	0.0060	2.33
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Volume per unit area (m <sup>3</sup> /ha)							
SRS		47.44	2.15	1.00	48.91	1.25	1.00
NC		49.75	1.53	1.99	48.78	1.17	1.13
LOG	RE <sub>A</sub>	47.32	1.37	2.47	49.12	1.09	1.32
LOG	RE <sub>V</sub>	46.97	1.31	2.71	48.62	1.06	1.37
LOG	RE <sub>A</sub> + RE <sub>V</sub>	47.57	1.35	2.54	49.12	1.09	1.32

NC approach with respect to increasing the precision of estimate of mean P and V. The largest RE<sub>p</sub> for the LOG approach was 63 percent greater than RE<sub>p</sub> for the NC approach for the Indiana study area and 51 percent greater for the Minnesota study area. The largest RE<sub>v</sub> for the LOG approach was 36 percent greater than RE<sub>v</sub> for the NC approach for the Indiana study area and 21 percent greater for the Minnesota study area.

As expected, for each study area the largest RE<sub>p</sub> was obtained for the LOG approach when the strata boundaries were selected to maximize RE<sub>p</sub>, and the largest RE<sub>v</sub> was obtained when the strata boundaries were selected to maximize RE<sub>v</sub>. The decrease in RE<sub>p</sub> when the strata boundaries were selected to maximize RE<sub>v</sub> was approximately 25 percent for both study areas, although the decrease in RE<sub>v</sub> when the strata boundaries were selected to maximize RE<sub>p</sub> was less than 10 percent for both study areas. Thus, RE<sub>p</sub> is apparently more sensitive to changes in strata boundaries than is RE<sub>v</sub>. When the strata boundaries were selected to maximize RE<sub>p</sub> + RE<sub>v</sub>, the relative decreases in both RE<sub>p</sub> and RE<sub>v</sub> for both study areas were less than 5 percent. Finally, very little advantage was realized for either study area when selecting strata boundaries to maximize RE<sub>p</sub> + RE<sub>v</sub> as compared to selecting them to maximize RE<sub>p</sub>.

## Conclusions

The LOG approach was superior to the NC approach for estimating both mean P and V for both study areas. Increases in RE<sub>p</sub> were 63 and 52 percent for Indiana and Minnesota, respectively, and increases in RE<sub>v</sub> were 36 and 21 percent for Indiana and Minnesota, respectively. Although selection of strata boundaries to maximize RE<sub>p</sub> + RE<sub>v</sub> rather than to maximize either RE<sub>p</sub> or RE<sub>v</sub> individually had a slight advantage, selection of boundaries to maximize RE<sub>p</sub> was nearly as effective.

Greater REs could possibly have been achieved with a few more strata for these data sets. However, the bimodal distributions of the plots (figs. 2a and 2b) with respect to  $\hat{P}$ , with most plots either completely forested or completely non-forested, suggest that the minimum of five plots per stratum would be difficult to achieve with larger numbers of strata, particularly for the smaller geographic areas for which the FIA program reports estimates.

Figure 2a.—Frequency distribution of Indiana study area plots.

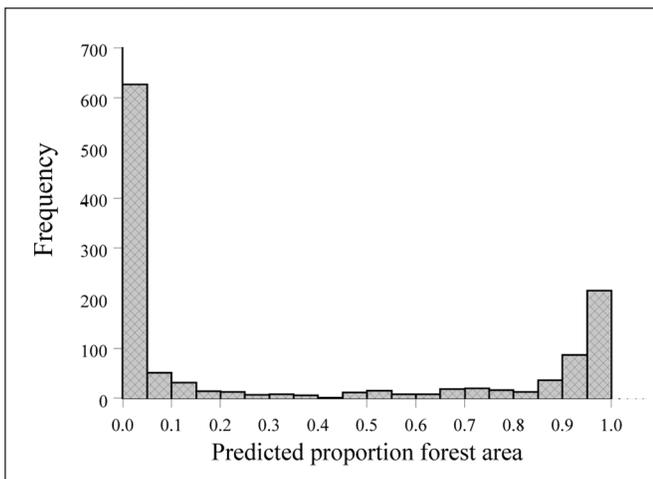
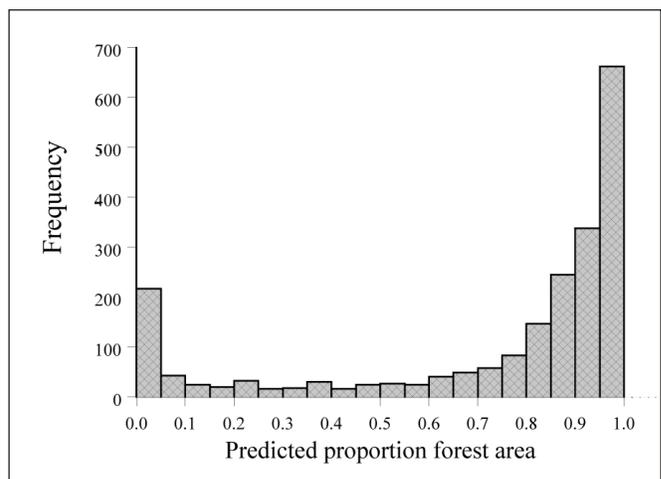


Figure 2b.—Frequency distribution of Minnesota study area plots.



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## Comparing Mapped Plot Estimators

Paul C. Van Deusen<sup>1</sup>

**Abstract.**—Two alternative derivations of estimators for mean and variance from mapped plots are compared by considering the models that support the estimators and by simulation. It turns out that both models lead to the same estimator for the mean but lead to very different variance estimators. The variance estimators based on the least valid model assumptions are shown to perform poorly in practice.

### Introduction

Mapped plots are an integral part of the U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) annual forest inventory design. The concept of mapping is intended to reduce the potential bias of having more than one forest condition on a single plot. The plot is mapped to indicate what proportion of the plot is covered by a particular condition. In the past, plots were moved or rotated into a uniform condition to avoid this problem. Plot rotation leads to a small bias in the estimates (Birdsey 1995), and mapping was believed to be a more statistically defensible approach (Hahn *et al.* 1995).

More than one estimator has been suggested for obtaining estimates of means and variances from mapped plots. Estimator 1 (EST1) is described in a FIA document (FIA 2004), and estimator 2 (EST2) is described in Van Deusen (2004). These estimators will be derived using a model-based approach and then compared.

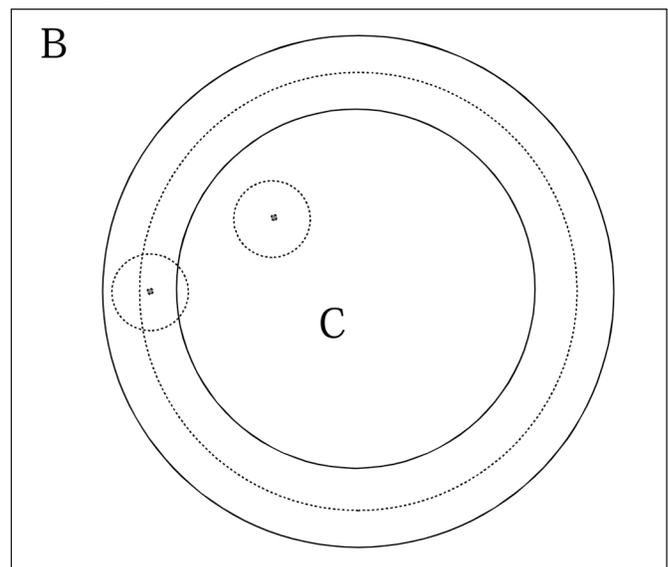
### Review of Theory

The FIA plot design consists of four circular subplots in a fixed configuration. Small diameter trees are measured only on smaller concentric plots in the larger subplots. Ignoring the specifics of the FIA plot design simplifies derivation of the estimators

without loss of generality. Therefore, the estimators are derived under the assumption that the sample plots consist of a single fixed-area plot.

The simple forest inventory model used in Van Deusen (2004) is followed here. Assume two conditions exist, C and B, where C is a circular condition surrounded by condition B (fig. 1). Estimates of the mean and variance of type C are of interest, and the other types that surround it are denoted as B. The shape of type C could be anything, in practice. Sampling is either systematic or simple random and uses fixed-area circular plots with radius  $d$ . The edge of type C is shown by a dash line, and a perimeter band that overlaps the outer edge of area C is shown by solid lines. The plot contains both conditions when the plot center falls within the perimeter band. The condition boundary is mapped when it crosses a plot.

Figure 1.—An area of condition C surrounded by condition B. Condition C is bounded by the dash line that is contained in a perimeter band of width equal to the diameter of the fixed-area circular plots. Plots with centers that fall within the band will contain some of both conditions. All other plots contain only one condition. One plot that is fully in condition C is shown along with a plot that overlaps the boundary. Plots that contain no C are not of interest.



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The following notation is similar to that used in Van Deusen (2004):

$a_i$  = The proportion of the area of plot  $i$  that is within condition C.

$n$  = The number of plots that contain some condition C.

$$\bar{a} = \sum_{i=1}^n a_i / n .$$

Where:

$y'_i$  = A variable that can be measured on each randomly located plot that completely or partially overlaps condition C. For plots that don't overlap C,  $y'_i = 0$ .

$y_i = y'_i/p_i$  is the original measurement expanded to a per acre (hectare) or total value.

$p_i$  = A value proportional to the selection probability of the plot, e.g., this would be 1/5 for a fifth-acre circular plot.

$\mu$  = The per unit area mean of variable  $y$  for condition C, e.g., cubic meter per hectare pine volume.

After a plot is located, the amount of variable  $y'$  is recorded and expanded to a per acre value,  $y$ . When plot  $i$  contains none of condition C,  $y_i = 0$ , and  $a_i=0$ . The  $n$  plots that contain a non-zero amount of condition C are labeled 1,...,n.

## Estimator Derivation

A model-based approach is used to derive mapped plot estimators. The estimators called EST1 and EST2 in the introduction are both derived in this section.

EST1 is derived first by starting with the following model:

$$y_i = \bar{a} \mu + e1_i \quad (1)$$

where  $e1$  is a random error term and  $E(e1_i, e1'_i) = \bar{a}^2 \sigma^2$ . This model states that the expanded plot value is equal to the mean per unit area value,  $\mu$ , multiplied by the average proportion of a plot,  $\bar{a}$ , that is in the condition of interest. The variance of the expanded plot value is proportional to the squared average proportion in the condition.

Consider the result of dividing equation (1) by  $\bar{a}$  to get the following equation:

$$y_i/\bar{a} = \mu + e_i \quad (2)$$

where  $E(e_i, e'_i) = \sigma^2$ . The transformed variable,  $\tilde{y} = y_i/\bar{a}$ , is the variable that the estimators in the "Stat Band" document (FIA 2004) are based on. Thus, the following estimators for mean and variance are based on this equation:

$$\bar{Y} = \frac{\sum_{i=1}^n \tilde{y}_i}{n} , \text{ and} \quad (3a)$$

$$v_1(\bar{Y}) = \frac{\sum_{i=1}^n \tilde{y}_i^2 - n \bar{Y}^2}{n(n-1)} \quad (3b)$$

These are standard mean and variance estimators that would apply to simple random or stratified random sampling without a finite population correction factor (Cochran 1977, Thompson 2002).

EST2 is derived from a related model that allows for plot values to vary according to the percentage of the plot falling in the condition:

$$y_i = a_i \mu + e2_i \quad (4)$$

where  $E(e2_i, e2'_i) = a_i \sigma^2$ . Equation (4) states that the amount,  $y_i$ , in the condition is related to the proportion,  $a_i$ , of the plot that falls in the condition. The variance of  $y_i$  is also proportional to  $a_i$ , which seems intuitively reasonable. Using standard least-squares formulas, the following are the estimators for the mean and variance (Van Deusen 2004):

$$\bar{Y} = \frac{\sum_{i=1}^n y_i}{\sum_{i=1}^n a_i} , \text{ and} \quad (5a)$$

$$v_2(\bar{Y}) = \frac{\hat{\sigma}^2}{\sum_{i=1}^n a_i} , \text{ where} \quad (5b)$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - a_i \bar{Y})^2}{\sum_{i=1}^n a_i - 1} \quad (5c)$$

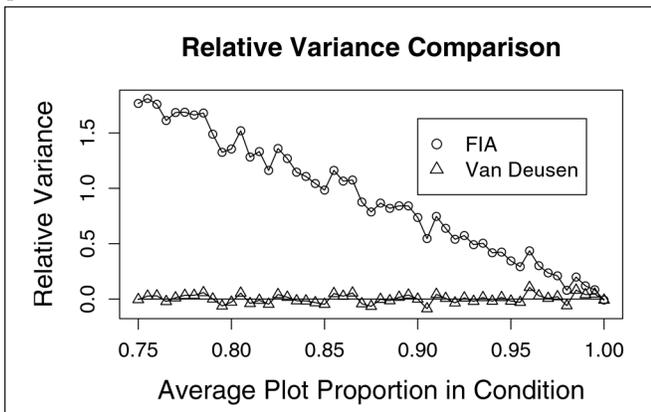
More detailed discussion about the derivation of equations (5b and 5c) can be found in Van Deusen (2004).

Note that equations (3a) and (5a) are identical because  $n\bar{a} = \sum a_i$ . The variance estimators, however, are quite different. Intuition suggests that  $v_2$  should be less than  $v_1$  because equation (4) is more flexible than equation (1). The exception is when all plots are fully in the condition so that  $\sum a_i = n$ , making equations (3b) and (5b) identical. In general, equation (1) is a crude model of the relationship between the plot values,  $y_i$ , and the proportions,  $a_i$ .

## Simulated Comparison

Simulated data are used to compare variance estimators  $v_1$  and  $v_2$ . The same simulation scheme used in Van Deusen (2004) is used here. Y-values are drawn from a normal distribution with standard deviation 300 and mean 1,000. There are 1,000 replications with 100 samples per replication. The average proportion of the plot in the condition area varies from 0.75 to 1.0. More simulation details are available in Van Deusen (2004).

Figure 2.—*Simulated comparison of two estimators for variance of the mean from mapped plots. A relative variance of 0 means the variance estimator was unbiased, a value of 1 means it predicted twice the actual variance, and a value of 2 means it predicted three times the actual variance.*



The simulation results in no noticeable bias in estimates of the mean (Van Deusen 2004), and the variance estimates are identical when  $\bar{a} = 1.0$ , as they should be. Variance estimator  $v_1$  deteriorates, however, as  $\bar{a}$  moves away from 1.0 (fig. 2). The relative variances (fig. 2) are computed as  $(\hat{v} - v)/v$ , where  $\hat{v}$  is the average of the estimated variances based on 100 observations from each of the 1,000 replications, and  $v$  is the simulated variance computed from the means of the 1,000 replications. A relative variance of 0 means the formula is unbiased, a value of 1 shows that the formula is predicting twice the variance that it should, and a value of 2 indicates that the formula is overpredicting by a factor of 3.

## Discussion

The simulation shows that the model that best describes the data produces the most accurate variance estimator, which is  $v_2$  in equation (5b). The model that led to  $v_1$  in equation (3b) is based on the notion that each plot measurement ( $y_i$ ) has the same expected value regardless of the plot proportion ( $a_i$ ) in the condition. Therefore, that this variance estimator performs poorly when plots have widely differing proportions within the condition is not surprising.

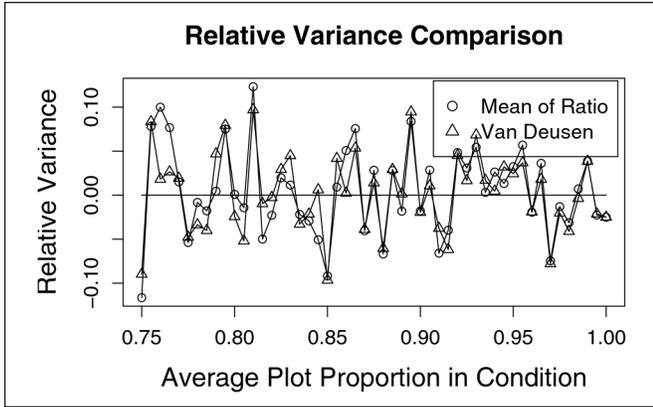
Other models might represent the data well that have not been considered here; therefore, no guarantee exists that equation (5b) is uniformly better than any alternative. For example, consider equation (4) with different variance assumptions on the error term,  $e_{2i}$ . Suppose the variance of the error was assumed to be a function of the squared proportion, i.e.

$E(e_{2i}, e_{2i}') = a_i^2 \sigma^2$ . This would lead to the following estimate of the mean:

$$\bar{Y}_2 = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{a_i} \quad (6a)$$

which is different from the mean estimator produced by the other models. A potential problem with this “mean of ratios” estimator is that plots with small  $a_i$  values are given large weights. Intuitively, this seems like a bad idea because these plots contain less information about the condition than a plot that is fully in the condition.

Figure 3.—Simulated comparison of two variance estimators defined by equations (5b) and (6b). The relative variance is as defined for figure 2.



The variance estimator for the ratio of means model is the following:

$$v(\bar{Y}_2) = \frac{\sum_{i=1}^n \dot{y}_i^2 - n \bar{Y}_2^2}{n(n-1)} \quad (6b)$$

where  $\dot{y}_i = y_i/a_i$ . This model was evaluated in the simulation described above, and it compared favorably (fig. 3) with equation (5b). The simulation included  $a_i$  values down to 0.5, so that no chance of dividing  $y_i$  by a miniscule  $a_i$  value was possible. Because equation (6b) doesn't perform any better than (5b) in this controlled situation, this equation is not recommended.

### Variance Estimator Is Unbiased

The purpose of this section is to prove that the variance estimator for EST2 is unbiased. Reconsider the assumption that the variance of the error term in equation (4) is proportional to  $a_i \sigma^2$ . Suppose a circular plot contains the variable of interest,  $y$ . If the coverage of the plot is absolutely homogeneous, the amount of  $y$ , say  $f(y)$ , on a proportion of the plot, would be  $f(y)=ay$ . This would lead to  $\text{Var}(f(y))=a^2\text{Var}(y)$ . Recall that  $0 \leq a \leq 1$  and therefore  $a^2 \leq a$ . In fact, the  $y$  variable will not be exactly homogeneous across the plot; therefore,  $a^2\text{Var}(y)$  would understate the variance of  $f(y)$ . A better approximation is likely to be  $\text{Var}(f(y))=a\text{Var}(y)$ . This is the justification for the assumption used in equation (4).

Intuitively, adjusting the degrees of freedom downward when using partial plots makes sense, and thus the denominator of variance estimator (5c) uses  $\sum a_i$  rather than  $n$ , the number of plots. Clearly,  $\sum a_i \leq n$ , with equality occurring when all plots are fully in the condition. Adjusting the degrees of freedom downward for partial plots results in an unbiased estimate of the mapped plot variance. Consider the variance estimator for mapped plots with known population mean,

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - \mu)^2}{\sum_{i=1}^n a_i} \quad (7)$$

The numerator of equation (7) could be written as  $\sum e_i^2$  and, by the variance assumptions for equation (4), this has expected value of  $\sigma^2 \sum a_i$ . Therefore, equation (7) is an unbiased estimator. Equation (5c) is also justified by this result because it has 1 degree of freedom subtracted from the denominator to account for the estimated population mean parameter.

In general, the sample size for mapped plots should be adjusted to account for only using a proportion of the plot,  $a_i$ . This makes sense intuitively and theoretically as shown for equation (5c). A plot that is only 50 percent in the condition should count half as much as a plot that is fully in the condition. This is the justification for dividing by  $\sum a_i$  rather than  $n$  in equation (5b).

### Conclusions

Mapped plots are being installed by FIA as part of the annual forest inventory system. Two estimators for means and variance that have been proposed elsewhere were re-derived and compared. It turned out that both estimators for the mean were identical, but the variance estimators were quite different. A simulation showed that the variance estimator from the literature (Van Deusen 2004) performed significantly better than the alternative estimator.

A mean of ratios estimator was also discussed. The mean of ratios variance estimator performed about as well as the estimator from the literature (Van Deusen 2004). The mean of ratios estimator, however, could perform badly if small slivers of plots are included in the analysis, and, therefore, is not a recommended estimator for this particular use.

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## Modifying Taper-Derived Merchantable Height Estimates to Account for Tree Characteristics

James A. Westfall<sup>1</sup>

**Abstract.**—The U.S. Department of Agriculture Forest Service Northeastern Forest Inventory and Analysis program (NE-FIA) is developing regionwide tree-taper equations. Unlike most previous work on modeling tree form, this effort necessarily includes a wide array of tree species. For some species, branching patterns can produce undesirable tree form that reduces the merchantable portion of the stem and merchantable heights to a fixed top diameter (e.g., 4 inches) are often unrealized. Thus, height estimates from a taper model tend to overestimate the actual merchantable length of the stem. This phenomenon is exacerbated as tree size increases. The extent of this problem is illustrated by comparing taper-derived merchantable height estimates to observed merchantable height measurements on trees from NE-FIA sample plots. Models were developed using individual tree attributes to adjust the taper-based estimates to account for reductions in merchantable height due to tree form.

### Introduction

The volume of the merchantable portion of a tree is one of the primary characteristics of interest obtained from a forest inventory. These volumes often are derived from height measurements at specified top diameter limits (e.g., 4 inches). Sometimes to improve inventory efficiency, these heights are estimated from height prediction equations (Ek *et al.* 1984) or tree taper models (Max and Burkhart 1976). These methods are satisfactory for species with growth tendencies toward relatively straight boles from ground to tip. Bias in merchantable height (and subsequent volume) predictions, however, occur for many species because

tree form can result in merchantable heights that are lower than the point where the specified diameter limit occurs.

For instance, taper equations are developed from paired height/diameter data obtained at various points along the tree bole. These data are obtained without regard to rules for determining the portion of the tree that may actually be used at a processing facility (e.g., minimum log length). Thus, assuming that the bole contains usable wood from the base to the model-predicted merchantable top height may be erroneous. For some species, the merchantable portion of the stem can often end at a point lower than where the top-diameter limit occurs. This occurrence is especially true for most hardwood species, where deliquescent form can produce relatively large decreases in diameter over a short distance. In these situations, the use of a taper-based system requires both model development and implementation strategies.

### Data

The data used for this research was obtained from U.S. Department of Agriculture (USDA) Forest Service Northeastern Forest Inventory and Analysis (NE-FIA) sample plots. Although NE-FIA collects a wealth of data at sample plots, the important measurements for this research are individual tree attributes. These variables include tree species, diameter at breast height (d.b.h.), total height, and bole height for trees 5.0 inches d.b.h. and larger. Bole height is defined as the first of (1) the point beyond which no 4-foot-long section can be produced because of excessive limbs, forks, or crooks, (2) a 4-inch top diameter, or (3) the point where the central stem terminates by branching before reaching 4-inch diameter (U.S. Department of Agriculture 2004). For this study, only data from sugar maple, red pine, and eastern white pine trees 5.0 inches d.b.h. and larger were used (table 1).

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Table 1.—Summary of tree data from NE-FIA sample plots for sugar maple, eastern white pine, and red pine.

Species/characteristic	N	Min.	Mean (standard deviation)	Max.
<b>Sugar maple</b>				
d.b.h. (in)	11,590	5.1	9.4 (3.7)	25
Bole height (ft)	11,590	4	36 (14.9)	99
Total height (ft)	11,590	17	59 (15.0)	125
<b>Eastern white pine</b>				
d.b.h. (in)	6,985	5.1	10.1 (4.3)	25
Bole height (ft)	6,985	4	37 (18.0)	99
Total height (ft)	6,985	12	52 (17.6)	125
<b>Red pine</b>				
d.b.h. (in)	905	5.1	9.0 (3.0)	22.2
Bole height (ft)	905	7	36 (18.0)	82
Total height (ft)	905	14	49 (17.2)	92

Additional data were available from an NE-FIA tree taper research project. In this regionwide study, measurements include tree diameter at 1, 2, 3, 4.5, and 6 feet of height. Additional diameter measurements are taken above 6 feet at approximate 1-inch taper decrements thereafter until a final measurement is obtained at tree tip (total height). These data were also subsetted to include only the three species listed in table 2.

## Analysis

One primary purpose of the NE-FIA taper research project is to eliminate the necessity for field crews to observe merchantable height attributes on sample trees. This elimination will not only improve data collection efficiency, but also result in better consistency over time and greater analytical flexibility. Merchantable height predictions from taper models, however, require a diameter limit to be specified. This necessity presents some difficulty for bole height prediction because the NE-FIA

Table 2.—Summary of tree data from NE-FIA taper project for sugar maple, eastern white pine, and red pine.

Species/characteristic	N	Min.	Mean (standard deviation)	Max.
<b>Sugar maple</b>				
d.b.h. (in)	66	3.1	10.9 (4.0)	29.9
Total height (ft)	66	25.2	58.7 (17.1)	90.2
No. of measurements	66	8	14 (4.0)	22
<b>Eastern white pine</b>				
d.b.h. (in)	63	3.1	12.3 (7.3)	36.3
Total height (ft)	63	18.1	59.1 (20.8)	102.2
No. of measurements	63	8	15 (5.2)	35
<b>Red pine</b>				
d.b.h. (in)	20	4.8	11.8 (5.5)	18.7
Total height (ft)	20	18.3	55.9 (16.1)	80.6
No. of measurements	20	9	16 (3.7)	23

data collection protocols incorporate limitations other than top diameter (e.g., minimum log length). Thus, bole height observations often are taken below the point where the 4-inch top limit occurs. This phenomenon can be illustrated by comparing observed bole height data to taper-derived heights at the 4-inch diameter limit.

For the purposes of this article, the model development strategy is simplified by adopting the segmented polynomial taper equation presented by Max and Burkhart (1976). The sugar maple, red pine, and eastern white pine data from the NE-FIA taper project were used to fit the following model for each species:

$$d^2/d.b.h.^2 = \beta_1(h/H - 1) + \beta_2(h^2/H^2 - 1) + \beta_3(\alpha_1 - h/H)^2 I_1 + \beta_4(\alpha_2 - h/H)^2 I_2 + \varepsilon \quad (1)$$

where:

d = diameter outside bark (in).

d.b.h. = diameter at breast height (in).

h = height (ft) at diameter d.

H = total tree height (ft).

$I_1$  = indicator (= 1 if  $\alpha_1 \geq h/H$ ; = 0 if  $\alpha_1 < h/H$ ).

$I_2$  = indicator (= 1 if  $\alpha_2 \geq h/H$ ; = 0 if  $\alpha_2 < h/H$ ).

$\alpha_1, \alpha_2$  = segment join points (estimated from data).

$\beta_{1-4}$  = parameters to be estimated from data.

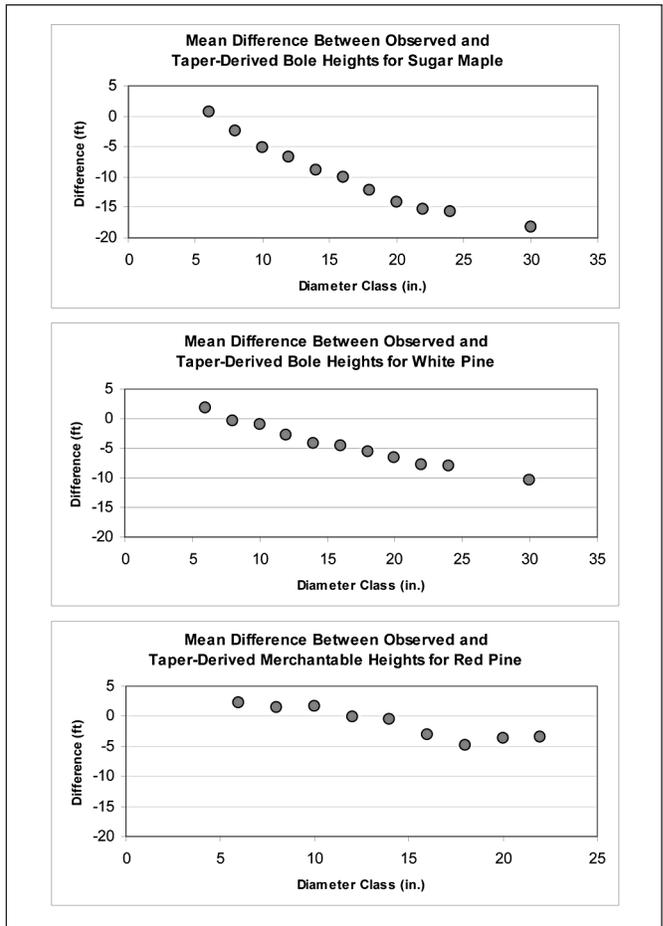
$\varepsilon$  = random deviation.

This model was chosen because it has been found to have better overall performance than many other taper models (Cao *et al.* 1980, Martin 1981). The model fit each species well, with  $R^2$  values of 0.92, 0.93, and 0.97 for sugar maple, eastern white pine, and red pine, respectively.

These fitted models were used to obtain predicted height to 4-inch top diameter for each tree in the NE-FIA inventory data. These three species were chosen to represent different “levels” of tree form. It was expected that the deliquescent tree form of sugar maple would result in observed bole height values occurring much lower than the 4-inch top limit. Conversely, the straight, single-stem growth tendency of red pine was expected to have bole height measures that were reasonably close to the point of 4-inches top. Eastern white pine was selected as a tree species that would have a form intermediate to the other two species.

For each species, the differences between the observed bole heights and heights predicted from the taper model were summarized by a 2-inch diameter class (fig. 1). Clearly, the differences between the observed and predicted heights become larger as tree d.b.h. increases. As surmised, the differences were greatest for sugar maple and smallest for red pine. When compared to observed data, the use of the taper-derived bole heights in conjunction with NE-FIA volume equations (Scott 1981) produce an overall increase in total volume of 10.6, 3.5, and 0.1 percent for sugar maple, eastern white pine, and red pine, respectively. These increases indicate that the development of taper models alone may not be sufficient for switching from observed field data to model-predicted values. Additional work is required to account for the effects of tree characteristics on predicted bole heights.

Figure 1.—Mean differences between observed and taper-derived bole heights by diameter class for sugar maple, eastern white pine, and red pine.



One approach was to model the differences between observed and predicted heights and apply these differences to the predicted values. Predicting the differences using individual tree attributes would allow for adjustments on an individual tree basis. Data were randomly split equally by species for modeling and validation purposes. To describe the differences for sugar maple trees, the following nonlinear model was fitted using least-squares regression techniques:

$$D = \hat{\alpha}_5 DBH^{\hat{\alpha}_6} \times \exp(\hat{\alpha}_7 DBH + \hat{\alpha}_8 H_{TCR}) + \epsilon \quad (2)$$

where:

D = difference (ft).

H<sub>TCR</sub> = height to crown (ft).

β<sub>5-8</sub> = parameters to be estimated from data.

Other variables as previously defined.

Model (2) did not perform well for prediction of differences in eastern white pine. A linear model was found to work best for the white pine data. In this formulation, significant predictor variables were d.b.h., crown ratio (CR), and height to crown:

$$D = \hat{\alpha}_9 + \hat{\alpha}_{10} DBH + \hat{\alpha}_{11} CR + \hat{\alpha}_{12} H_{TCR} + \epsilon \quad (3)$$

where:

CR = Crown ratio (%).

β<sub>9-12</sub> = parameters to be estimated from data.

Other variables as previously defined.

A linear model approach also worked well for red pine. In this case, however, different predictor variables were statistically significant. CR and H<sub>TCR</sub> were no longer important independent variables. Total tree height was not a significant variable for difference prediction for eastern white pine but was useful for prediction for red pine trees:

$$D = \hat{\alpha}_{13} + \hat{\alpha}_{14} DBH + \hat{\alpha}_{15} H + \epsilon \quad (4)$$

where:

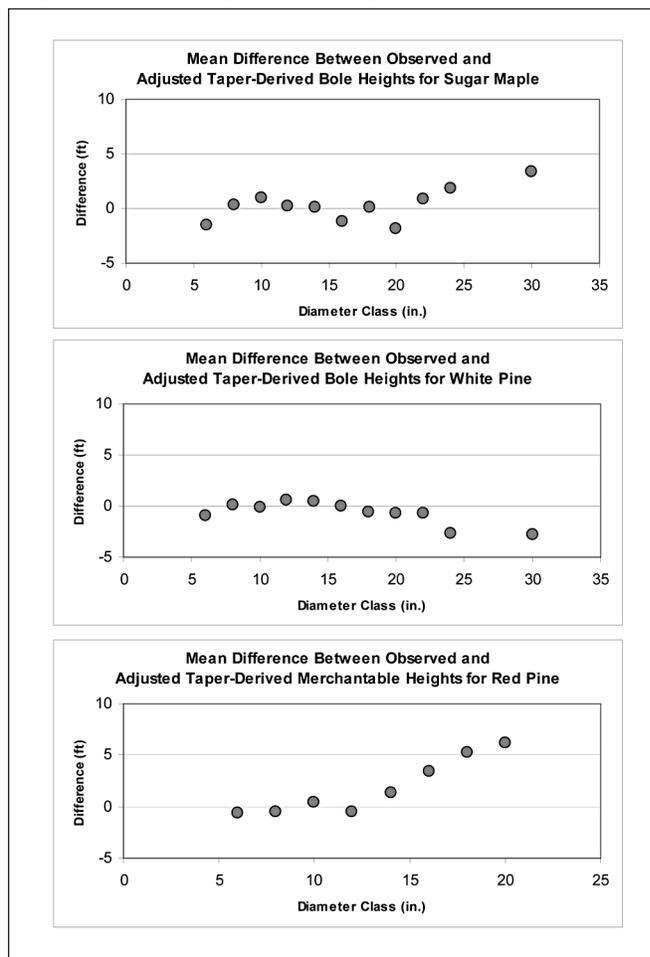
β<sub>13-15</sub> = parameters to be estimated from data.

Other variables as previously defined.

For each model (2–4), examination of plots of residuals (observed minus predicted) versus predicted values and residuals versus model predictors indicated no systematic problem with model specification or heteroscedasticity.

As anticipated, the large variability in the data was reflected in the fit statistics. R<sup>2</sup> values were approximately 0.30 for all three models. Model standard errors were 6.2, 4.9, and 3.9 for sugar maple, eastern white pine, and red pine, respectively. The application of the models to the validation data significantly affected the differences between observed and taper-derived bole heights (fig. 2). Improved agreement between predicted and observed bole heights was noted for both sugar maple and eastern white pine. For red pine, better agreement was obtained for the smaller

Figure 2.—Mean differences between observed and model-adjusted taper-derived bole heights by diameter class for sugar maple, eastern white pine, and red pine.



diameter classes, but agreement was generally poorer for the larger diameter classes. An investigation into this behavior revealed that differences between observed and taper-derived bole heights for the larger few diameter classes were greater in the fit data than in the validation data. In addition, relatively few observations exist in the larger diameter classes. These “distant” points can have a significant influence on the slope of the regression line. When applied to the validation data, the result was overprediction of the difference for larger diameter classes that produced adjusted bole heights that were too small.

The differences between the volumes computed from observed data and those from adjusted taper-derived heights were reduced significantly for sugar maple and white pine. Due to the issue mentioned above for red pine, the differences increased. The volume differences were 0.3, – 0.4, and 1.0 percent for sugar maple, eastern white pine, and red pine, respectively. For sugar maple, the volume difference between observed data and taper-derived bole heights was statistically significant ( $p < 0.0001$ ) when evaluated using a paired t-test, but the difference using adjusted heights was not significantly different ( $p = 0.3758$ ). Results of the eastern white pine analysis show that the use of adjusted heights reduced the difference by nearly 90 percent, although the difference from observed data was still significant from a statistical standpoint ( $p = 0.0009$ ). As expected, the bole characteristics of red pine resulted in nonsignificant volume differences computed from observed and taper-derived bole heights ( $p = 0.7899$ ). The use of adjusted heights had the undesirable effect of producing a volume estimate that was different from the observed data ( $p = 0.0117$ ). Table 3 summarizes results for all three species.

## Discussion/Conclusion

For two of the three species studied, a modeling approach to adjusting the taper-derived heights was effective in terms of obtaining close agreement between volume estimates. The model forms and predictor variables that provided the best predictive ability, however, were not consistent across the three species studied. Species-specific models that differ in form and content are difficult to implement in inventories in which many species are encountered. Limiting the number of models may be possible, however, by creating groups of species with similar form characteristics. This approach requires further investigation.

Another issue raised by the analysis is whether an adjustment equation is needed for all species. For red pine, only a 0.1-percent difference between volumes from observed data and volumes based on heights predicted from the taper model (without adjustment) existed, although an offsetting trend occurred between positive and negative values. One could argue that this discrepancy is not large enough to warrant application of an adjustment model. In our analysis, the use of the adjustment model did not have the anticipated effect, and results were poorer. At this point, how to determine the necessity for application of an adjustment model to taper-derived merchantable heights is unclear.

Taper-based merchantable height estimates for certain species should account for tree form characteristics if merchantability is not defined solely by a top diameter limit. Taper-derived merchantable height estimates can be modified to account for individual tree characteristics. In this study, variables assumed to be well-correlated with tree form characteristics (e.g., branching)

Table 3.—Evaluation of differences in volume between observed data and taper-derived bole heights, and between observed data and adjusted taper-derived bole heights for sugar maple, eastern white pine, and red pine.

Species	Taper-derived bole height					Adjusted taper-derived bole height			
	N	Mean difference (ft <sup>3</sup> )	Standard error	t	p-value	Mean difference (ft <sup>3</sup> )	Standard error	t	p-value
Sugar maple	5,795	682	19.8	34.44	< 0.0001	11	12.3	0.89	0.3758
Eastern white pine	3,491	244	11.4	21.37	< 0.0001	– 29	8.6	– 3.32	0.0009
Red pine	452	– 4	16.6	– 0.27	0.7899	– 52	20.5	– 2.53	0.0117

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were used as predictors to model differences between observed and taper-derived bole heights. Appropriate model forms and/or significant predictor variables, however, appeared to be species specific. In addition, the need to apply an adjustment model may be questionable for some species. Other approaches to modifying taper-derived merchantable heights include average reductions by diameter class (or some other tree characteristic), indirect manipulation through increases in estimates of cull, and incorporation of modifiers directly within the taper equation. More research is needed to determine a modification method that is both accurate and easy to implement.

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## New Method for Determining the Relative Stand Density of Forest Inventory Plots

Christopher W. Woodall and Patrick D. Miles<sup>1</sup>

**Abstract.**—Determining the relative density of Forest Inventory and Analysis plots is complicated by the various species and tree size combinations in the Nation's forested ecosystems. Stand density index (SDI), although developed for use in even-aged monocultures, has been used for stand density assessment in large-scale forest inventories. To improve application of SDI in uneven-aged, mixed species stands present in large-scale inventories, a model was developed whereby a stand's maximum SDI was a function of the stand's mean specific gravity (SG) of individual trees. A strong relationship was found between the mean SG of all trees in a stand and the 99<sup>th</sup> percentiles of the observed distribution of stand SDIs. A model is proposed whereby the mean SG of individual trees in a stand serves as a predictor of a stand's maximum stocking potential, regardless of the stand's diameter distribution and species composition.

Assessing the relative density of hundreds of thousands of forest inventory plots across the Nation is complicated by the diameter distributions, species compositions, and site conditions unique to every forest stand. Most techniques for assessing relative stand density were developed for application in individual stands consisting of monocultures or regionally common species mixtures (Reineke 1933, Krajicek *et al.* 1961, Gingrich 1967, Drew and Flewelling 1979). Although a substantial body of literature addresses the development of small-scale, stand-specific relative density measures, scant research has been conducted to develop effective relative density assessment techniques for use at strategic scales inclusive of all tree species and size combinations.

Stand density index (SDI) is a method for estimating relative stand density. SDI was first proposed by Reineke (1933) as a

stand density assessment tool based on size-density relationships observed in fully stocked monocultures. SDI is defined as the equivalent trees per hectare at a quadratic mean diameter of 25 cm and is formulated as the following:

$$SDI = tph (d.b.h./25)^{1.6} \quad (1)$$

where *SDI* is stand density index, *tph* is number of trees per hectare, and *d.b.h.<sub>q</sub>* is quadratic mean diameter (cm) at breast height (1.4 m) (Long 1985). The only way to appropriately determined SDI in stands with Gaussian diameter distributions is to use the summation method (Long and Daniel 1990, Shaw 2000, Ducey and Larson 2003) by which the SDIs for individual diameter at breast height (d.b.h.) classes are added for the entire stand. The SDI summation method is formulated as follows:

$$SDI = \sum tph_i (d.b.h._i/25)^{1.6} \quad (2)$$

where *d.b.h.<sub>i</sub>* is the midpoint of the *tph<sub>i</sub>* diameter class (cm), and *i*th is the number of trees per hectare in the *i*th diameter class (Long 1995, Shaw 2000).

The SDI of even-aged monocultures is typically compared to an empirically observed, species-specific maximum SDI for determining a stand's relative density. Maximum SDI (*SDI<sub>max</sub>*) is defined as the maximum possible density for a given mean tree size in a self-thinning population (Long 1996). *SDI<sub>max</sub>* has typically been determined strictly through empirical means, finding the heaviest stocked stand on the landscape. Percentages of species' *SDI<sub>max</sub>* have been related to prominent stages of stand development (Long 1985), making their determination valuable for strategic-scale assessments of stocking. A relative density of 25 percent of *SDI<sub>max</sub>* is associated with the onset of competition, 35 percent of *SDI<sub>max</sub>* is associated with the lower limit of full-site occupancy, and 60 percent *SDI<sub>max</sub>* is associated with the lower limit of self-thinning (Long and Daniel 1990).

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SDI has rarely been applied in mixed species stands (Binkley 1984, Puettman *et al.* 1993, Torres-Rojo and Martinez 2000, Williams 2003) because of a lack of empirical and theoretical information. In most studies, investigators were able to empirically determine SDI for specific forest types in local areas but were unable to state any broader conclusions (Binkley 1984, Puettman *et al.* 1993, Williams 2003). As an alternative to empirically determining  $SDI_{max}$  for mixed species stands, past research in monocultures suggests that  $SDI_{max}$  may be predicted using species' specific gravities (SGs; Dean and Baldwin 1996). Dean and Baldwin (1996) suggest that species-specific variation in the maximum mechanical leverage canopies exert on stems may help explain species variation in  $SDI_{max}$ . They found that species' SG was inversely related to  $SDI_{max}$ . The  $SDI_{max}$  versus SG relationship has not been further explored or applied in stand inventory/management activities and may serve as a novel methodology for estimating  $SDI_{max}$ . Therefore, the goal of this study is to develop and validate a technique for estimating  $SDI_{max}$  for stands containing diverse tree species and size combinations using the mean specific gravities ( $SG_m$ ) for individual trees.

## Methods

Plot data from the national Resources Planning Act (RPA) database were used as observations in this study (Smith *et al.* 2004). The RPA database contains plot and tree data collected by the Forest Inventory and Analysis (FIA) program of the U.S. Department of Agriculture (USDA) Forest Service. Briefly, the plot design for FIA inventory plots consists of four 7.2-m, fixed-radius subplots spaced 36.6 m apart in a triangular arrangement with one subplot in the center of the triangle. All trees located on forested subplots with a d.b.h. of at least 12.7 cm are inventoried. (For further information on the RPA database and FIA sample design, refer to Smith *et al.* (2004) and Bechtold and Patterson [in press].) The study data set consisted of data from all fully forested plots ( $n = 119,235$ ) from the RPA database that had at least one tree of the selected eight species representing diverse growth conditions and forest ecosystems across the United States: loblolly pine (*Pinus taeda*), ponderosa pine (*Pinus ponderosa*), Douglas fir (*Pseudotsuga menziesii*), paper birch (*Betula papyrifera*), trembling aspen (*Populus tremuloides*),

white oak (*Quercus alba*), lodgepole pine (*Pinus contorta*), and red maple (*Acer rubrum*) ( $n = 119,235$ ). A validation data set was created using all fully forested inventory plots ( $n = 29,307$ ) from the RPA database that did not contain any of the study tree species.

For all study plots, the *tph* and *SDI* (equation [2]) for 10-cm d.b.h. classes were determined for study species and other species in each plot. The SG for all study trees was based on data available from the USDA Forest Service Forest Products Lab (U.S. Department of Agriculture, Forest Service 1999). The relationship between the 99<sup>th</sup> percentile SDI ( $SDI_{99}$ ) for classes of  $SG_m$  (0.015  $SG_m$  class width, 26 classes) for the study data set was modeled as follows:

$$E(SDI_{99}) = b_0 + b_1(SG_m) \quad (3)$$

where  $E(\cdot)$  is statistical expectation,  $SG_m$  is the mean SG for all trees per plot, and  $b_0$  and  $b_1$  are parameters to be estimated.  $SDI_{99}$  was used instead of  $SDI_{max}$  as the response variable because the process of modeling  $SDI_{max}$  relationships can be highly affected by outliers. Therefore, for predicting  $SDI_{max}$  based on mean stand SGs,  $SDI_{99}$  serves as a surrogate for  $SDI_{max}$ . The ability of the regression model (equation [3]) to estimate  $SDI_{max}$  was evaluated using the validation data set by predicting  $SDI_{99}$  for  $SG_m$  classes (0.025  $SG_m$  class width, 13 classes) and computing relative residuals [(observed – predicted)/observed].

## Results/Discussion

The ability of  $SG_m$  to predict  $SDI_{max}$  was evaluated for the  $SDI_{99}$  within classes of  $SG_m$ . For predictions of  $SDI_{99}$ ,  $SG_m$  explained 92 percent of the variation ( $\hat{b}_0 = 2057.3$ ,  $\hat{b}_1 = -2098.6$ ) (fig. 1, table 1). The model's ability to predict  $SDI_{99}$  was evaluated using the validation data set. Analysis of the relative residuals for the 13 classes indicates a slight bias of the estimated linear relationship so that the  $SDI_{99}$  may be overpredicted (table 2, fig. 2). The mean of the relative residuals was 0.05 (table 2). The absolute mean of relative residuals for the 13 validation data set classes of  $SG_m$  was 0.08 (table 2).

Figure 1.—99<sup>th</sup> percentile SDIs by mean stand SG for over 119,000 RPA plots.

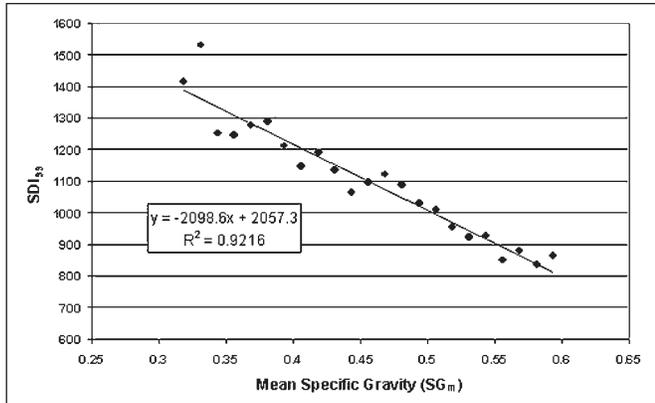


Figure 2.—Relative residuals for predictions of SDI<sub>99</sub> for validation data set SG<sub>m</sub> classes.

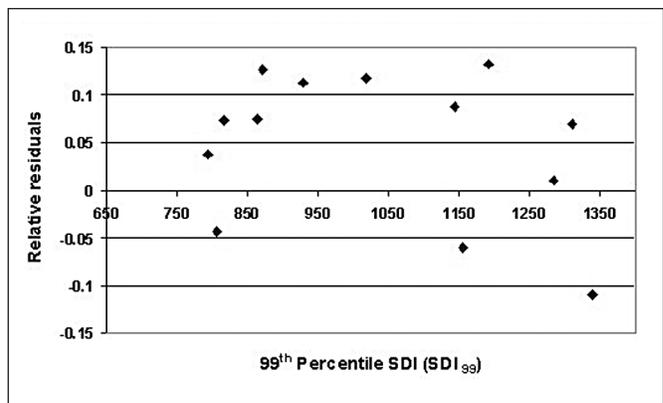


Table 1.—Maximum observed and 99<sup>th</sup> percentile stand SDs for 119,235 RPA plots by classes of mean stand SG.

Mean SG classes	Number of sample plots	Maximum observed stand SDI	99 <sup>th</sup> percentile observed stand SDI
0.3126–0.3250	855	2,819	1,413
0.3251–0.3375	1,697	1,908	1,529
0.3376–0.3500	3,546	1,814	1,252
0.3501–0.3625	4,894	2,285	1,242
0.3626–0.3750	5,884	1,775	1,275
0.3751–0.3875	11,056	2,640	1,288
0.3876–0.4000	6,084	1,883	1,210
0.4001–0.4125	5,470	1,951	1,145
0.4126–0.4250	5,290	2,162	1,190
0.4251–0.4375	5,149	1,718	1,134
0.4376–0.4500	5,750	2,075	1,062
0.4501–0.4625	4,678	1,811	1,095
0.4626–0.4750	8,478	1,704	1,120
0.4751–0.4875	7,030	1,396	1,087
0.4876–0.5000	6,491	1,309	1,026
0.5001–0.5125	6,150	1,347	1,009
0.5126–0.5250	5,928	1,266	951
0.5251–0.5375	5,592	1,299	921
0.5376–0.5500	4,891	1,507	923
0.5501–0.5625	3,961	1,403	848
0.5626–0.5750	3,133	1,417	876
0.5751–0.5875	2,514	1,439	834
0.5876–0.6000	1,546	1,404	865

Table 2.—Observed and predicted 99<sup>th</sup> percentile SDIs for 29,307 RPA validation plots for 13 classes of mean stand SG.

Weighted mean SG classes	Number of sample plots	Observed 99 <sup>th</sup> percentile SDI	Predicted 99 <sup>th</sup> percentile SDI	Relative residuals <sup>a</sup>
0.3001–0.3250	1,637	1,310	1,401	0.07
0.3251–0.3500	1,214	1,191	1,349	0.13
0.3501–0.3750	1,987	1,284	1,297	0.01
0.3751–0.4000	1,714	1,144	1,244	0.09
0.4001–0.4250	2,210	1,339	1,192	– 0.11
0.4251–0.4500	1,367	1,019	1,139	0.12
0.4501–0.4750	2,780	1,156	1,087	– 0.06
0.4751–0.5000	2,606	929	1,034	0.11
0.5001–0.5250	2,994	872	982	0.13
0.5251–0.5500	5,445	864	929	0.08
0.5501–0.5750	3,245	817	877	0.07
0.5751–0.6000	1,602	794	824	0.04
0.6001–0.6250	506	807	772	– 0.04

<sup>a</sup> Relative residuals = (observed – predicted)/observed.

Because the majority of past SDI research focused solely on pure species stands (Reineke 1933, Stage 1968, Long 1985, Sterba and Monserud 1993, Woodall *et al.* 2003), self-thinning relationships underlying SDI has been assumed to be affected by mixed species compositions. Values of SDI<sub>max</sub> that guide SDI application in stand-stocking assessments are always listed by single species (Long 1985). Unfortunately, vast acreages of forests of the United States are covered by mixed species stands. A finding from Dean and Baldwin (1996) forms the basis of our attempt to develop a method for estimating more stand-specific SDI<sub>max</sub>. Dean and Baldwin (1996) found that a species' SG was inversely related to its SDI<sub>max</sub>. The same result was found in our study. We attempted to take this premise a step farther and determine the mean SG for all trees in a stand, regardless of species. Results indicated a relationship between SDI<sub>99</sub> and SG<sub>m</sub> for classes of SG<sub>m</sub>. Validation of our model to predict a stand's SDI<sub>99</sub> based on its SG<sub>m</sub> indicated a slight bias toward overpredicting SDI<sub>99</sub> (0.08). The nearly 29,000 plots in the validation data set, however, represent unique combinations of uncommon tree species across the United States (e.g., Osage-orange [*Maclura pomifera*] and Ohio buckeye [*Aesculus glabra*]) in which trying to determine a SDI<sub>max</sub> would be nearly impossible using other methodologies.

Methods for assessing relative stand density in strategic-scale assessments may be augmented by the results of this study. By using the summation method to determine current stand SDI and SG<sub>m</sub> to predict SDI<sub>99</sub> as a surrogate for SDI<sub>max</sub>, we may quantify relative stand density across the Nation regardless of a stand's species and tree size combinations. SDI methods presented in this study warrant future refinement and application in strategic-scale density assessment situations such as found in national fire hazard reduction efforts.

## Conclusions

The SDI<sub>max</sub> that may be attained by any individual stand is affected by the stand's species composition and size distribution. Because SDI<sub>max</sub> may be unique for individual stands, a stand-specific model is suggested to predict SDI<sub>max</sub>. The SG of individual species may be used to define the stem mechanics driving self-thinning dynamics resulting in a stand-specific SDI<sub>max</sub>. This study found a relationship between the SDI<sub>99</sub> by classes of mean stand SG and SG<sub>m</sub> of all trees in a stand. If SG<sub>m</sub> may be considered a predictor of SDI<sub>99</sub>, as a surrogate for SDI<sub>max</sub>, relative densities of individual stands may be estimated across large scales, regardless of diameter distributions and species compositions.

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### **Additional Readings**

Long, J.N.; Smith, F.W. 1984. Relation between size and density in developing stands: a description and possible mechanism. *Forest Ecology and Management*. 7: 191–206.

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## Post-Modeling Histogram Matching of Maps Produced Using Regression Trees

Andrew J. Lister<sup>1</sup> and Tonya W. Lister<sup>2</sup>

**Abstract.**—Spatial predictive models often use statistical techniques that in some way rely on averaging of values. Estimates from linear modeling are known to be susceptible to truncation of variance when the independent (predictor) variables are measured with error. A straightforward post-processing technique (histogram matching) for attempting to mitigate this effect is presented, and a comparison with untransformed model estimates is made. Histogram matching enhanced the contrast visible in the final map and produced estimates that mimicked the range of estimates in the original data set but performed worse overall with respect to absolute error of prediction. Examples of cases where histogram matching might be an effective post-processing method are given.

### Introduction

Advances in computer software and hardware have increased the prevalence of spatial predictive modeling of ecological data. Modeling methods range from simple spatial interpolation to sophisticated linear and nonlinear multivariate techniques. Most of the techniques that are commonly applied rely on averaging procedures. For example, simple linear interpolation generally involves defining a search radius around areas to be estimated and applying the average value of the attribute of known data within that radius to the area. Similarly, linear modeling approaches such as regression rely on averaging of deviations from a “best fit” line to arrive at parameter estimates. In nearly all cases, either the estimate itself is an average or part of the parameter estimation process is based on averaging. This trait

of linear modeling can lead to a compression of the variance of the set of estimates if the independent (predictor) variables are measured with error (Curran and Hay 1986).

In the linear regression context, the predictor variables are assumed to be measured without error (Montgomery and Peck 1982). Curran and Hay (1986), however, provide a concise review of reasons why this assumption is not true in remote sensing studies. The effects of errors in the predictor variables in multiple regression have been well documented (Curran and Hay 1986, Whitemore and Keller 1988, Elston *et al.* 1997). Generally, the parameter estimates are underestimated, leading to an underestimation of large values and an overestimation of small values (Curran and Hay 1986, Cohen *et al.* 2003), resulting in a compression of the variance of the set of estimates relative to that of the training data.

In this article, satellite and other geospatial data are used to predict biomass (megagrams aboveground dry biomass [not including foliage] per hectare) in Maine, using U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) plot information as training data. FIA has a network of inventory plots across the country and collects and reports information on the status of and trends in the Nation’s forest resources (Gillespie 1999). Due to the nature of the data sets (very small plot area to pixel area ratios, smoothed predictor data, lack of strong functional relationships between the dependent and predictor data), the predictions obtained by a regression tree approach (Quinlan 1993) had truncated variance. This article describes a post-processing technique—histogram matching—that attempts to deal with this systematic overprediction in the lower tail and underprediction in the upper tail of the distribution of training data.

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## Methods

Data from 2,210 FIA plots collected in Maine between 1999 and 2003 were used in the study.<sup>3</sup> The distribution of plots in the study area is based on a hexagonal tessellation with one FIA plot randomly located in each 2,428.2-ha hexagon. Each FIA plot consists of four circular 14.6-m (48-ft)-diameter subplots, with one subplot located in the center and three equidistant subplots distributed symmetrically around and located 31.6 m (120 ft) from the center subplot. The subplots occupy 0.07 ha (0.17 ac), and the subplot array can be subtended by a circle of 0.4 ha (1.0 ac) in area. The value of the total aboveground dry biomass was calculated from live tree data collected on each plot using equations found in Wharton *et al.* (1997).

The predictor data used were contained in a multilayered ERDAS IMAGINE image and consisted of 271 250-m resolution layers, including multitemporal and monthly composites and derived indexes of imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS)-satellite-borne sensor (Justice and Townsend 2002), several rasterized summaries of the State Soil Geographic soils database compiled by the USDA Natural Resources Conservation Service (1994), summaries of the land cover classes found in the National Land Cover Data (NLCD) database (Vogelmann *et al.* 2001), mean monthly and annual temperature and precipitation from the PRISM climate database (Daly *et al.* 2004), rasterized Bailey's Ecoregions (Bailey 1996) and U.S. Geological Survey NLCD 2001 mapping zone (which is similar to an ecoregion map) (Homer and Gallant 2001), a rasterized grid representing distance to streams (U.S. Geological Survey 1999), and various derivatives of the National Elevation Dataset (Gesch *et al.* 2002).<sup>4</sup>

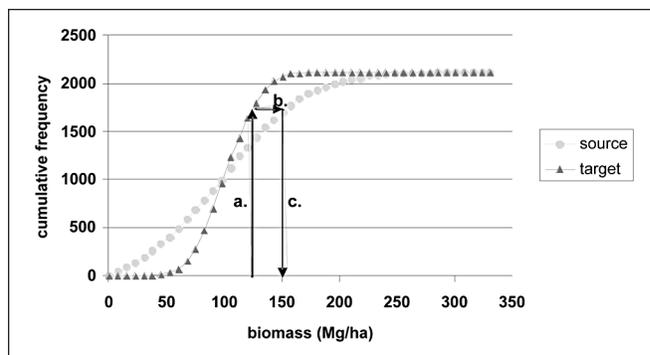
Leica Geosystems' ERDAS IMAGINE image processing software was used to extract values for each of the predictor layers at the locations where the 2,210 FIA plots used in the analysis were located. Cubist regression tree software was used to derive regression tree models of forest biomass. These models then

were applied to the stack of predictor layers in ERDAS IMAGINE to create a set of spatially referenced model predictions. To create a validation data set, 220 plots were randomly withheld from the Cubist modeling.

Histogram matching was applied to the output map generated by Cubist and ERDAS IMAGINE so that its frequency distribution of pixel values matched that of the training data. In the histogram-matching technique, a lookup table that specifies the relationship between the cumulative distribution function of a source histogram and a target histogram is generated. Using that lookup table, the target data are transformed so that their distribution matches that of the source data. (For a description of histogram matching, see fig. 1.)

Histogram matching is typically used to standardize raw satellite images that were acquired at different times and under different conditions to facilitate mosaicking of the images or classifications

Figure 1.—Example of histogram matching applied to the biomass estimates produced from Cubist modeling in Maine. To generate a lookup table, the cumulative frequency histograms of the actual data (source) and the predictions (target) were generated. A lookup table was generated as follows: for a given biomass value in the actual data (e.g., 125 Mg/ha below), the cumulative frequency was determined (a) and related to the corresponding cumulative frequency (b) and value (e.g., 150 Mg/ha below) (c) of the predicted data. The lookup table built in this manner was used to reclassify the map of predictions so that its frequency distribution matched that of the original data.



<sup>3</sup> U.S. Department of Agriculture (USDA), Forest Service. 2000. Field data collection procedures for phase 2 plots. In: Forest inventory and analysis national core field guide, version 1.4. Internal report on file at: USDA Forest Service, Washington Office, FIA, 1601 North Kent Street, Suite 400, Arlington, VA 2220. Vol. 1.

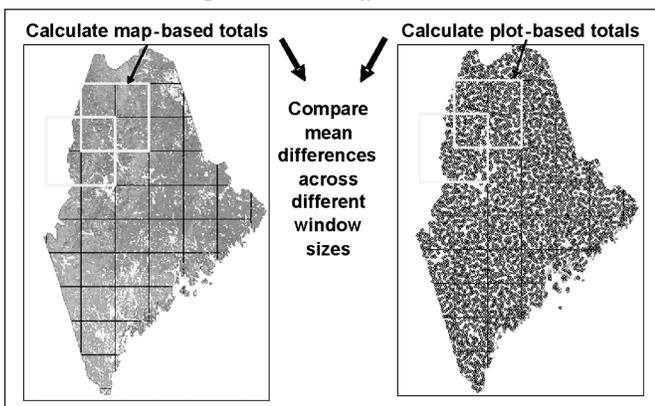
<sup>4</sup> Complete details of the steps used to prepare the data and data derivatives are on file at the USDA Forest Service, Northeastern Research Station, 11 Campus Blvd, Ste. 200, Newtown Square, PA 19073.

conducted on the images (e.g., Homer *et al.* 1997). Cohen *et al.* (2001) used histogram matching as a post-processing approach to facilitate the post-classification juxtaposition of images acquired under different conditions. In the current study, however, we resorted to a post-processing approach for pragmatic reasons. FIA has currently chosen to operationally use a modeling protocol that relies on the Cubist regression tree approaches, which can produce outputs with truncated variance (Curran and Hay 1986).

Graphs of biomass on the 221 test plots versus the predicted values were produced, and the relationship between the set of actual and both sets of predicted values (uncorrected and histogram-matched) was described using a simple, first-order linear regression equation and associated coefficient of determination ( $R^2$ ). In addition, mean absolute error (MAE) was calculated. To assess the efficacy of histogram matching with respect to removing the overestimation and underestimation that occurred in the tails of the distribution of original data, the slope of the regression, the  $R^2$  and the MAE were compared.

In addition to global comparisons, a multiscale analysis of the mean absolute difference between the average biomass of the plots found in sets of grid cells superimposed over the area and the pixel-based estimates in those cells was calculated for each of a number of spatial scales (fig. 2). The goal of this analysis

Figure 2.—Square grid cells of varying sizes (15 x 15, 19 x 19, 22 x 22, 25 x 25, 35 x 35, 50 x 50, 71 x 71, 87 x 87, and 100 x 100 km) were superimposed on the study area. In each grid cell, the mean value for biomass on the plots and that for the pixel-based estimates was determined, and differences were calculated and compared across different window sizes.



was not only to characterize the spatial agreement between the pixel-based estimates and the actual values, but also to reveal the scale at which biomass varied across the landscape.

## Results and Discussion

Figure 3 shows a map of the uncorrected and histogram-matched biomass estimates. The estimates depicted in figure 3a (the uncorrected data) show less variability than those shown in figure 3b (the histogram-matched data). The histograms of estimates support this (fig. 4)—the range of values found in the uncorrected estimates is much narrower than that of the histogram-matched estimates and the actual plot data. In many situations, duplication of the variability found in the actual data is a desirable trait of a map of modeled estimates because it makes a map of the estimates more useful.

Table 1 gives a comparison of the simple linear regression parameters, the MAE and the  $R^2$ . Figure 5 depicts scatterplots of the actual versus uncorrected prediction and actual versus histogram-matched prediction. The parameters (slope and y intercept) and diagnostic information (MAE) from the simple linear regression analyses indicate that the histogram-matching procedure performed better with respect to producing estimates

Figure 3.—(a) Biomass map produce by Cubist modeling without post-processing. (b) Map produced by histogram matching of the map in (a) so the frequency distribution of pixel values matched that of the training data set.

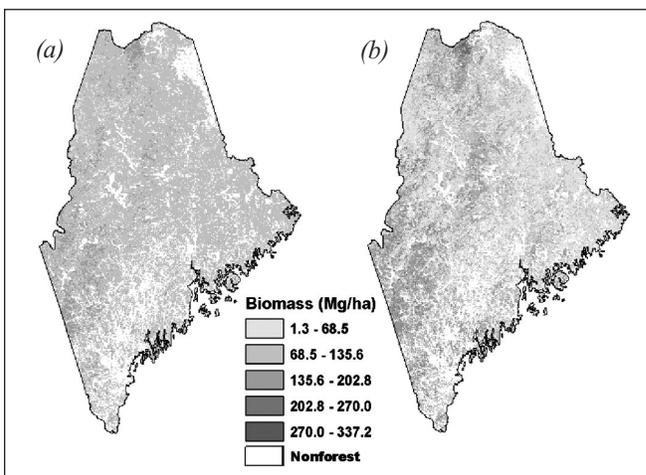


Figure 4.—Frequency histograms of the training (actual) data set, the original prediction, and the histogram-matched (post-processed) prediction. The variance of the original predictions is truncated, whereas that of the histogram-matched data matches that of the actual data.

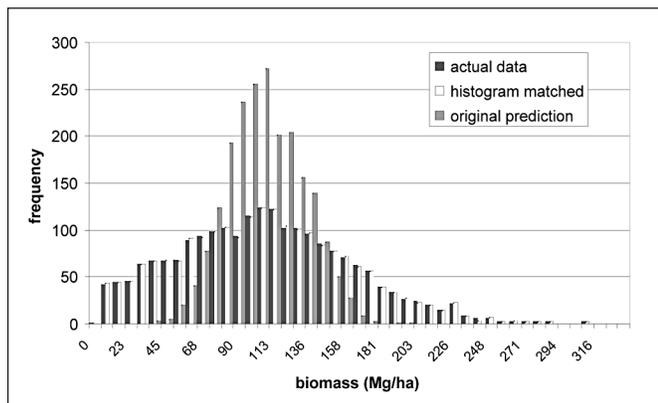
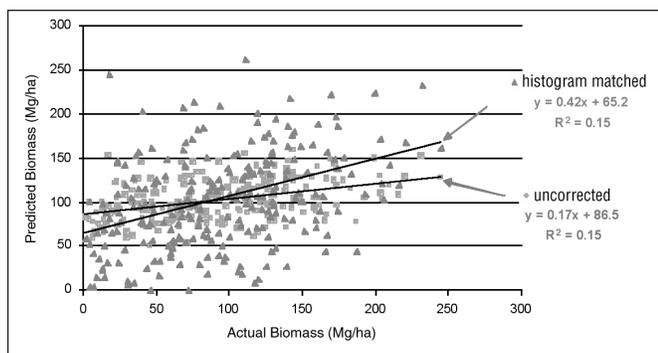


Figure 5.—Scatterplots of the original (red circles) and histogram-matched (green triangles) values versus the validation data withheld from the Cubist modeling ( $n = 221$ ). Simple linear regression lines describing the scatterplots indicate that the set of histogram-matched predictions more closely follow a 1:1 line than do the uncorrected estimates.



that followed a 1:1 observed versus predicted line. The uncorrected estimates, however, performed better overall (the MAE of the histogram-matching data was 20 percent higher than that of the uncorrected data). An analysis of the MAE per decile of the actual data (table 2) indicates that the histogram-matching procedure only performed better in the lowest and highest deciles because the procedure stretched out the distribution of predictions and thus lowered the variance in the tails of the distribution. This stretching led to the poorer performance of histogram matching in deciles near the median, however, because a wide range of uncorrected values was transformed into output values close to

Table 1.—Overall comparison of MAE of the uncorrected (original) and the histogram-matched (post-processed) predictions.

	Uncorrected	Histogram-matched
MAE	39.70	47.70
slope	0.17	0.42
intercept	86.50	65.20
R <sup>2</sup>	0.16	0.15

Table 2.—Per decile comparison of the simple linear regression parameters and diagnostics of the uncorrected (original) and the histogram-matched (post-processed) predictions.

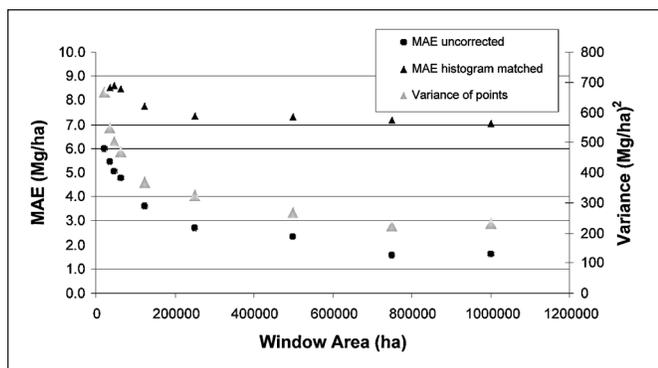
Percentile	MAE uncorrected	MAE histogram-matched
10	75.2	56.2
20	62.3	61.8
30	38.9	39.3
40	33.3	42.0
50	22.8	43.4
60	17.6	42.5
70	17.3	41.2
80	22.4	40.7
90	33.7	49.9
100	71.8	59.5

the median (note the steep slope of the target histogram near the median [fig. 1]). If maintenance of the full range of variability of actual data is wanted, histogram matching appears to be a valid option. The tradeoff, however, is overall lower accuracy for the resulting set of estimates.

Figure 6 shows results of the multiscale analysis of agreement between plot-based and pixel-based estimates. The figure indicates that a similar pattern of decreasing MAE as the size of the analytical windows increased from 23,400 to 1,000,000 ha. Although the uncorrected data set agrees much better with the FIA plots at each scale, the patterns of decrease are the same, suggesting that the relative interpretability of the spatial distribution of biomass on both maps at different resolutions is similar.

The variance of the window-based means (calculated across all windows at each resolution) (fig. 6) shows a decrease in plot variance as the analytical window increases in size. Because the MAE follows a very similar pattern, the decline in MAE with

Figure 6.—MAE (absolute value of average biomass/ha of FIA plots—average biomass/ha of pixels) computed for the uncorrected and the histogram-matched estimates at several scales. The variance of the window-based means of the plots is shown for each window size is also shown (yellow triangles, secondary y axis).



increasing window size is probably driven by the convergence of the window-based means on the global mean as the analytical window size approaches the size of the entire study area. In other words, as the window size increases, the number of plots per window increases, the variance of the biomass decreases, and the mean biomass in the windows approaches the global mean. Because the maps of predictions reflect the variability of biomass across the landscape, they follow this same pattern.

A notable feature of figure 6 is the rate of decrease in MAE (and plot-based variance) as window size increases. At a certain spatial scale (approximately 500,000 ha), increasing window size leads to only a small corresponding dip in MAE or variance, suggesting that this is similar to the scale of spatial autocorrelation of biomass in this area (Isaaks and Srivastava 1989). This information could be useful when designing sampling protocols or studying regional scale trends in biomass-related processes.

Ideally, FIA would either adapt its modeling approach or use input data that are less prone to measurement error. For example, the resolution mismatch between the plot data and the predictor

data could be addressed. Statistical methods other than regression trees, which rely in part on linear modeling, also could be used. Future research could thus involve using more robust techniques and predictor data with more of a functional relationship with the plot data. Practically speaking, however, FIA currently cannot produce regional- and national-scale maps without implementing the Cubist-ERDAS IMAGINE approach and without using coarse-scale data. The Cubist- ERDAS IMAGINE approach offers many benefits, including computational efficiency, ease of use, and batch processing options. Similarly, the coarse-scale data are inexpensive, easily acquired, and manageable in terms of storage space and processing requirements. On the other hand, FIA's methods do not leave much room for altering the modeling protocol, hence the appeal of a straightforward post-processing attempt to correct systematic errors.

This article illustrates the use of histogram matching as a post-processing method. The technique did not improve the overall accuracy of the map but could contribute to other potential map uses. It allowed for the transformation of biomass predictions so that their frequency distribution matched that of a target distribution (herein, that of the FIA data). It created a map that showed more contrast, revealing the visual spatial pattern in the data set more effectively than the uncorrected estimates. It performed worse overall in terms of MAE but performed better at making predictions in the tails of the distribution of training data. This predicting ability can be a desirable trait for a modeling data set. For example, if rare events are of interest, the depiction of predictions that fall into the rare category, such as areas with biomass greater than 300 Mg/ha, might aid the land manager seeking to identify areas with old growth forest or unique ecological characteristics. It also helps the map user understand the overall spatial pattern of biomass across the landscape. The disadvantage of the histogram-matching approach is the potential loss of reliability of the map as a whole. In the case of biomass maps, the specific interests of the user should thus be taken into account when selecting a modeling technique and any post-processing methods.

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# Considerations in Forest Growth Estimation Between Two Measurements of Mapped Forest Inventory Plots

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**Abstract.**—Several aspects of the enhanced Forest Inventory and Analysis (FIA) program’s national plot design complicate change estimation. The design incorporates up to three separate plot sizes (microplot, subplot, and macroplot) to sample trees of different sizes. Because multiple plot sizes are involved, change estimators designed for polyareal plot sampling, such as those used for horizontal point sampling, is still required. The differences between two such estimators FIA has favored in the past are discussed. The condition-class mapping feature of the new design further complicates change estimation. These complications are discussed, and alternatives to simplify the design are proposed.

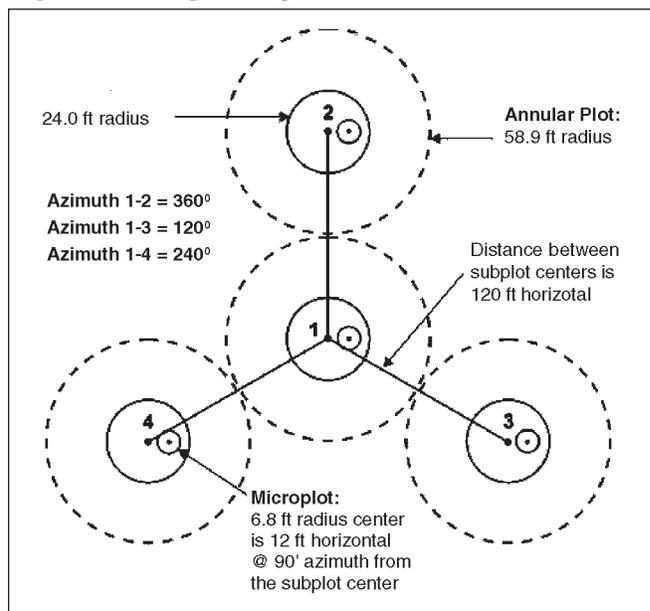
## Introduction

The U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) program uses a mapped, fixed-plot design as part of its national core sampling protocols (Hahn *et al.* 1995). Each ground plot contains a cluster of four points spaced 120 feet apart (fig. 1). Each point is surrounded by a 24-foot, fixed-radius subplot where trees 5.0 inches diameter at breast height (d.b.h.) and larger are measured. All four subplots total approximately 1/6<sup>th</sup> of an acre. Each subplot contains a 6.8-foot, fixed-radius microplot where saplings (1.0–4.9 inches d.b.h.) and seedlings are measured. All four microplots total approximately 1/75<sup>th</sup> of an acre. Each subplot is surrounded by a 58.9-foot, fixed-radius macroplot, which can be useful for sampling rare occurrences such as large trees (e.g., greater than 40.0 inches d.b.h.). All four macroplots total approximately 1 acre.

To enable division of the forest into various domains of interest for analytical purposes, the tree data recorded on these plots must be properly associated with the area classifications. To accomplish this, plots are mapped by condition class. Field crews assign an arbitrary number (usually 1) to the first condition class encountered on a plot. This number is then defined by a series of predetermined discrete variables attached to it (i.e., land use, forest type, stand size, regeneration status, tree density, stand origin, ownership group, and disturbance history). Additional conditions are identified if a distinct change occurs in any of the condition-class variables on the plot.

Sometimes a plot straddles two or more distinct condition classes. Boundaries between condition classes can bisect the subplots, or they can be located between the subplots. Microplots and macroplots (if used) are mapped in a similar fashion. Thus,

Figure 1.—Basic plot design.



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for each ground plot, the microplot, subplot, and macroplot area in each condition class is known, as are the location and condition class of every tree tallied.

One objective of the FIA program is to assess forest growth (gross growth, net growth, and net change) and forest change (land clearings, reversions and encroachment, forest condition changes). The mapped-plot design introduced new challenges in change assessment. This article examines the situations unique to the mapped-plot design and discusses considerations that may affect estimates of forest growth and forest change.

## Forest Growth

FIA generally recognizes at least four components of growth; these are usually expressed in terms of growing-stock or all-live volume, where  $t$  is the initial inventory of a measurement cycle, and  $t + 1$  is the terminal inventory, and are listed as follows:

$S$  = survivor growth—the change in volume of live trees at time  $t$  that survive until time  $t + 1$ .

$I$  = ingrowth—the volume of trees at the time that they grow across the minimum diameter threshold between time  $t$  and time  $t + 1$ . The estimate is derived at the size of trees at the threshold (1.0 inch d.b.h. for all-live volume and 5.0 inches for growing-stock volume). The diameter thresholds are usually measured at breast height, but for shrub-like trees designated as “woodland species” in the Western United States, diameter at root collar (d.r.c.) is the measure employed. Growth on ingrowth is the change in volume of ingrowth trees between the time they reach the threshold diameter and time  $t + 1$ .

$M$  = mortality—the volume of trees that die due to natural causes between time  $t$  and time  $t + 1$ .

$C$  = cut—the volume of trees that were removed due to harvesting activity between time  $t$  and time  $t + 1$ .

These components are used to explain the difference in inventory volumes ( $V_t$  and  $V_{t+1}$ ) between time  $t$  and time  $t + 1$ . One desirable feature in broad-scale inventories is change estimators that are additive (i.e., the previous inventory plus the net change sums to the new inventory). To be additive, the estimators for each component of growth on the right side of the equation (Meyer 1953),

$$V_{t+1} - V_t = S + I - M - C,$$

must sum to the difference of the estimators of the left side values. This additive feature is referred to as *compatibility*. Total compatibility in broad-scale inventories is never ensured, however, partly because of intersurvey population differences caused by additions to or deletions from the forest land base, protocol changes (e.g., species added or deleted), and previous misclassifications by field crews.

FIA usually reports estimates of change for growing-stock volume (live trees 5.0 inches d.b.h. and larger at time  $t$  that meet the definitions of growing stock). For the growing-stock case, only the subplot is used in the estimation process at time  $t$  and time  $t + 1$ , so most estimators reduce to the same result. Some regions, however, use the optional macroplot. Situations also exist in which the attribute of interest is all-live volume (where the diameter threshold is 1.0 inch) and requires data from the microplot. If both the microplot and subplot are involved, the plot design is biareal; if the macroplots are also involved, the plot design is triareal. Any change estimation involving more than one plot size is polyareal sampling, and the same techniques required for permanent horizontal point sample apply.

FIA units have historically used one of two methods for computing change from horizontal point samples—the methods proposed by Beers and Miller (1964) and Van Deusen *et al.* (1986). These and several other estimators were considered for use in FIA's National Information Management System. The Beers-Miller estimator was ultimately selected as the national default for FIA because of its intuitive simplicity (Bechtold and Patterson, in press).

The Beers-Miller estimator weights all survivor growth ( $S$ ) on the plot size at time  $t$ , which is analogous to “fixing the plot

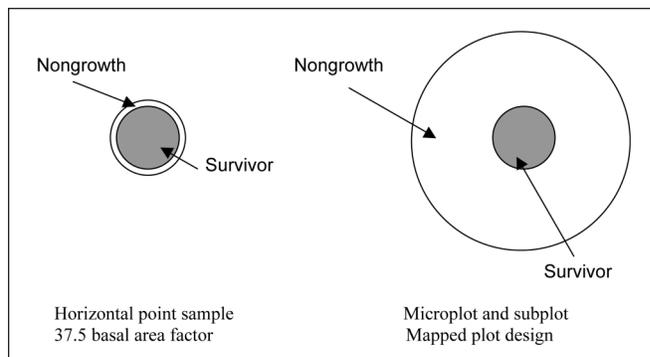
size” at the time of the initial inventory. This estimator excludes “nongrowth trees” from the definition of survivor growth. Nongrowth trees are defined as subplot trees outside the microplot and at least 5.0 inches in diameter at time  $t + 1$  and at least 1.0 inch at time  $t$ . The Van Deusen estimator weights  $S$  based on the plot size where growth occurs (i.e., at time  $t$  and time  $t + 1$ ) and includes nongrowth trees. This procedure was preferred by some FIA units because of the compatibility attained by incorporating the nongrowth trees excluded by the Beers-Miller procedure.

Roesch (1988) outlines a procedure that “fixes the plot size” at the end of the inventory period. The procedure includes nongrowth trees, and their growth is estimated. For FIA inventory purposes, the procedure would predict the attributes for computing a nongrowth’s tree volume at time  $t$ , such as d.b.h. and bole length. The procedure is considered unbiased if the estimator of the time  $t$  values of the trees in the nongrowth sample is unbiased.

Although all three techniques are unbiased, the Beers-Miller approach has been criticized because of its lack of compatibility. The previous inventory plus the net change do not sum to the current inventory because all the weighting is based on initial tree size to compensate for the exclusion of the nongrowth component. If compatibility was a major concern for at least some FIA regions when traditional horizontal point samples were used, it continues to be an issue for FIA’s current biareal and triareal plot designs. If one is interested in using the information contained in the sample of nongrowth to attain compatibility, one should consider an estimator other than the Beers-Miller approach.

Figure 2 illustrates the relative selection circles for trees that were less than 5.0 inches d.b.h. at time  $t$  and grew to a d.b.h. of 5.1 inches at time  $t + 1$  for a horizontal point sample and the FIA’s biareal design (microplot and subplot). The shaded inner circle represents the initial selection probability of a microplot (1/300<sup>th</sup> of an acre) for both plot types. The outer circle represents the terminal selection probability. For a horizontal point sample with a basal area factor of 37.5, a 5.1-inch d.b.h. tree would represent approximately 264 trees per acre, whereas the same size tree would represent 24 trees per acre on the subplot. The abrupt drop in the per acre value for a  $S$  tree growing from the

Figure 2.—Selection circles for nongrowth trees for a horizontal point sample and a microplot and subplot for the mapped plot design.



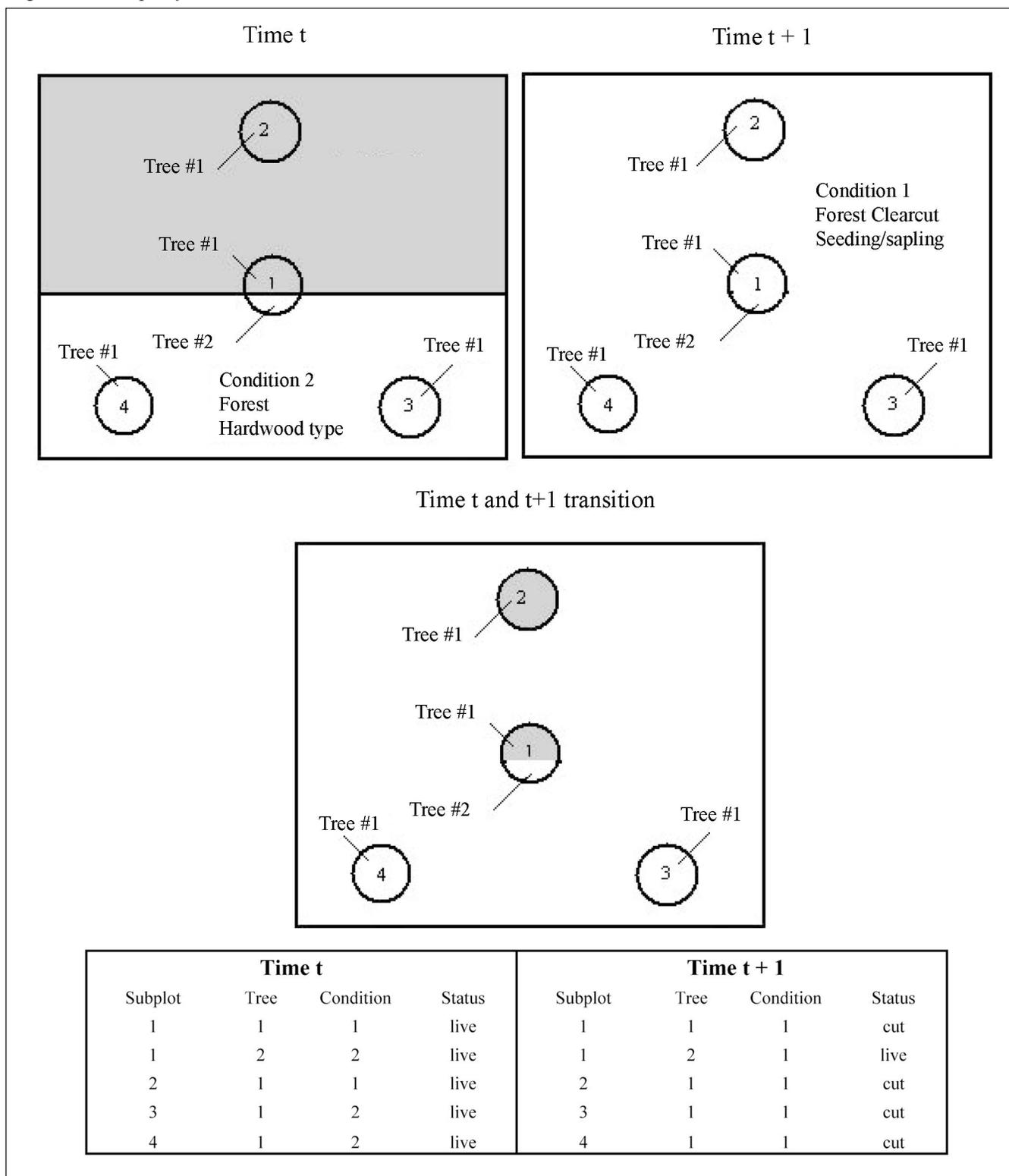
microplot on to the subplot would result in a significant negative survivor growth value for an individual tree if the Van Deusen approach was used.

The magnitude of the difference between growth estimators will depend on the number of trees in the nongrowth sample representing additional information. If the population of trees is varied, and nongrowth trees are only a small part of the population of interest, all three growth procedures should yield about the same estimate of survivor growth. Suppose instead that the population of trees is even-aged, and the basal areas of the trees are heavily clustered about the threshold between the microplot and the subplot. In this latter case, the nongrowth sample becomes significant. This situation is fairly common in regions where intensive forest management produces young, rapidly growing, planted pine stands.

The mapped-plot design poses another challenge for forest growth estimates because the shape and area of condition classes change over time. This design complicates the partitioning of growth, removals, and mortality by condition-class parameters at either time  $t$  or time  $t + 1$ . Summarizing timber removal volume by condition -class parameters such as forest type, stand origin, and ownership at the time of the initial inventory is usually desirable in broad-scale reporting.

Consider the following example. Figure 3 illustrates a situation where at time  $t$ , a plot was separated into two forest conditions, a hardwood and a softwood stand. Between time  $t$  and time  $t + 1$ ,

Figure 3.—Example of condition classes at time  $t$ , time  $t + 1$ , and associated transition matrix.



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the stand was harvested resulting in one condition at the second visit. The table in figure 3 indicates the subplot, tree number, condition number, and tree status assignment at the two points in time. The shaded area in the time  $t$  and time  $t + 1$  transition illustration indicates the position of the two previous conditions in relation to the current condition. Visually, a condition class transition matrix is produced by overlaying a map of each subplot at time  $t$  with a similar map of the same subplot at time  $t + 1$ . A population estimate of removal volume by previous forest type requires a condition indicator assigned at time  $t$  to all trees assigned a tree status of cut at time  $t + 1$ .

The previous condition numbers of all remeasured trees are automatically available from the data collected at time  $t$ ; however, in some cases the assignment of previous condition to new trees (missed, ingrowth, and nongrowth trees) requires additional effort. The assignment of previous conditions to new trees can be automated for subplots that had no boundaries at time  $t$ , but for subplots with previous boundaries, the previous condition numbers of new trees may need to be assigned in the field. This aspect of mapped plots has the potential to increase measurement error associated with change estimation. The extra fieldwork could be avoided by using a computer algorithm such as the one developed by Bechtold *et al.* (2003), which uses geometry to superimpose a previous condition map over the coordinates of new trees, but at least some of the automated assignments (i.e., trees close to boundaries) still need to be manually checked when the data are processed.

In addition to the extra fieldwork and/or processing requirements, another major consideration associated with the mapped plots is how the database will be structured for temporal comparisons. Linking plot-level, condition-level, or tree-level data between two points in time can be cumbersome, if not impossible, if certain coding schemes change. Adopting a procedure that may not be as accurate but eases the burden on the information management effort may be simpler.

The following two alternatives for assigning a previous condition to remeasured trees would eliminate the need for a complicated simulation procedure and be simple to apply in the field or office:

1. Plot-level approach. All remeasured trees on the plot at time  $t + 1$  are assigned the condition value of plot center at time  $t$ . The condition assignment to a remeasured tree remains the same at time  $t + 1$ . A slight modification to this approach would be to assign a condition value associated with the predominant condition at time  $t$ —i.e., the previous single condition with the highest area percent of the plot area. This would alleviate the occasional situation where a road, right-of-way, or other small feature passes through plot center.
2. Subplot-level approach. All remeasured trees on the plot at time  $t + 1$  area are assigned the condition value at subplot center at time  $t$ . The condition assignment to a remeasured tree remains the same at time  $t + 1$ . A slight modification to this approach would be to assign a condition value associated with the predominant condition at time  $t$ —i.e., the previous single condition with the highest area percent of the subplot area. This would alleviate the occasional situation where a road, right-of-way, or other small feature passes through subplot center.

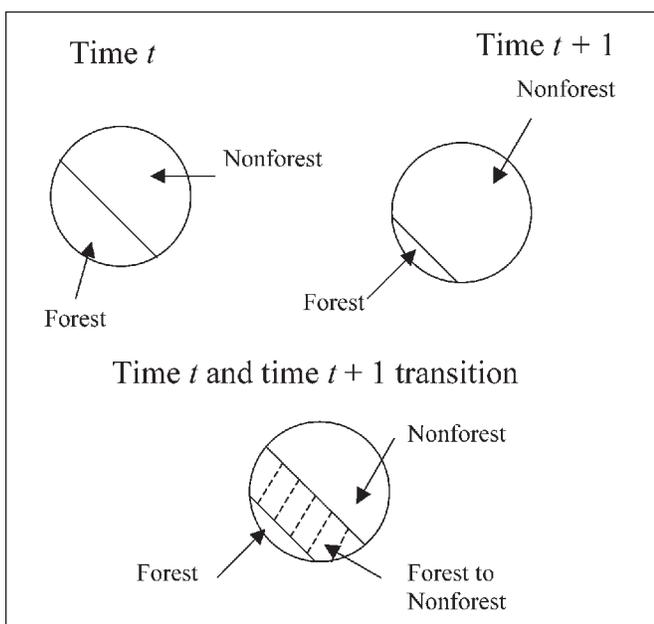
## Forest Area Change

Forest area change may be defined as the difference in the aggregate acreage of forest or stand area based on the remeasurement of the same area at two points of time. FIA typically uses a two-phase sampling approach for estimates of forest area where a large sample of photo points or pixels are interpreted to assign strata for a smaller sample of ground plots (Cochran, 1963). Quantifying changes in forest populations over time is usually accomplished by changes measured on field plots. Having a measure of new forest land coming into the land base (such as reversions and encroachment) and forest land leaving the land base (such as forest land being converted to urban or agricultural land use) are often desirable, as is tracking certain stand conditions over time for ecological monitoring and trend analysis. For example, FIA has often produced estimates of acres harvested, regenerated, or disturbed for various stand classifications such as forest type, stand origin, and ownership. Estimates associated with change are usually stratified by the classification assigned at time  $t$ .

The procedures to accomplish forest area change estimates are similar to those described for assigning remeasured trees to condition class, except the attribute of interest is area instead of volume. Figure 4 illustrates a common occurrence in which the edge of a forest-nonforest boundary has changed between two points in time on a subplot, a typical situation along the edges of agricultural fields or alongside roads where small amounts of forest land have been cleared. The crosshatched area in the time  $t$  and  $t + 1$  transition indicates the actual area that has been cleared. If this small amount of land area can be quantified, and an area percent can be developed, this proportion could be applied to a total land area figure to determine the amount of acreage that was cleared.

If the plot map from time  $t + 1$  is superimposed over the map from time  $t$  to estimate change, several considerations become evident. First, a distinction between real change, field crew error, and measurement error must be made. Subtle changes in boundary delineation due to measurement error could result in absurdly small change polygons that are meaningless for analysis purposes. In the figure 4 example, suppose the change was due to nothing other than field crew error at time  $t$  or time  $t + 1$ ?

Figure 4.—Example of forest land being cleared on a subplot, with condition classes at time  $t$ , time  $t + 1$ , and associated transition matrix.



Should error be treated as real change, or should it be identified and corrected? Second, because an infinite number of shapes are possible when a subplot mapped at time  $t$  is overlaid with its counterpart at time  $t + 1$ , database management could become unwieldy if condition-level observations are needed for every polygon created by change. Third, scale is always an important consideration in broad-scale inventories. Does FIA really need to identify small areas at a scale smaller than a subplot? Is it worth the time and effort to develop the field procedures, algorithms, simulation techniques, and databases to accommodate very small changes that occur on plots or subplots?

The following are two alternatives to the fully mapped approach:

1. Plot-level approach. All forest area change estimates are based on the assignment of the condition value at plot center at time  $t$  and time  $t + 1$ . The approach assumes only one condition exists at the plot level at both points in time. A slight modification to this approach would be to assign a condition value associated with the predominant condition at time  $t$  and time  $t + 1$ —the single condition with the highest area percent of the plot area. This would alleviate the occasional situation where a road, right-of-way, or other small feature passes through plot center.
2. Subplot-level approach. All forest area change estimates are based on the assignment of the condition value at subplot center at time  $t$  and time  $t + 1$ . The approach assumes only one condition exists at the subplot level at both points in time—up to four per plot location. A slight modification to this approach would be to assign a condition value associated with the predominant condition at time  $t$  and time  $t + 1$ —the single condition with the highest area percent of the subplot area. This would alleviate the occasional situation where a road, right-of-way, or other small feature passes through subplot center.

## Discussion

Several possible estimators are available for growth of survivor trees when the fully mapped plot design is remeasured. Whatever procedure is selected, incorporating computation of

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two or more of the estimators in the analysis of remeasured mapped plot design data is suggested. Further analysis may be needed when evaluating trends in components of change. Many regions will be comparing estimates of growth, removals, and mortality from remeasured mapped plot data to estimates from earlier inventories in which horizontal point samples were used.

The alternative procedures suggested for quantifying forest change and assigning a previous condition classification to trees would simplify the data compilation process, but they have shortcomings. The plot-level approach can obviously result in bias in classification of change. For instance, a plot that is subdivided into a pine and hardwood condition at time  $t$  could result in significant numbers of trees being assigned to an incorrect condition classification (such as softwoods getting assigned to a hardwood forest type). The plot-level approach could yield acceptable results in regions with broad-scale homogenous conditions where very little condition changes are occurring on the plots. The subplot-level approach will give a more refined estimate of forest change than the plot-level approach assuming that boundary mapping on subplots is not occurring frequently. The most comprehensive evaluation of different alternatives should consist of compiling inventory data for a large region or a State and analyzing differences in population estimates using the different approaches including available mathematical simulation techniques.

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