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Inventory methods for trees in nonforest areas in the great plains states

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Abstract The US Forest Service's Forest Inventory and Analysis (FIA) program collects information on trees in areas that meet its definition of forest. However, the inventory excludes trees in areas that do not meet this definition, such as those found in urban areas, in isolated patches, in areas with sparse or predominantly herbaceous vegetation, in narrow strips (e.g., shelterbelts), or in riparian areas. In the Great Plains States, little is known about the tree resource in these noninventoried, nonforest areas, and there is a great deal of concern about the potential impact of invasive pests, such as the emerald ash borer. To address this knowledge gap, FIA's National Inventory and Monitoring Applications Center has partnered with state cooperators and others in a project called the Great Plains Initiative to design and implement an inventory of trees in nonforest areas. The goal of the inventory is to characterize the nonforest tree resource using methods compatible with those of FIA so a holistic understanding of the resource can be obtained by integrating the two surveys. The goal of this paper is to describe the process of designing and implementing the survey, including plot and sample design, and to present some example results from a reporting tool we developed.

Keywords Trees outside forest · Nonforest tree inventory · Emerald ash borer · Great Plains forest inventory · Multiphase sample · National Inventory and Monitoring Applications Center · Great Plains Initiative

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Introduction

The Agricultural Research, Extension, Education and Reform Act of 1998 (16 USC 1642(e)) called for the US Forest Service's Forest Inventory and Analysis (FIA) program to conduct annual forest inventories. The law mandates that FIA conduct a comprehensive and consistent forest inventory using a core set of measurements across all lands and ownerships, that 20% of inventory plots in each state be measured each year, that the data and analyses are made available annually, and that comprehensive state forest resource assessments be produced every 5 years.

FIA plots are distributed relatively uniformly across a grid of cells formed by a hexagonal tessellation of the nation, with each plot representing at most 2,428 ha. Data collected on each plot include information on land use and ownership type. Tree-level and certain forest and site-level attribute data are collected only on portions of plots that meet FIA's definition of forest: areas that are at least 0.4 ha in size, have certain geometric properties (e.g., at least 36.6 m wide), are at least 10% current or former stocking level, and are not subject to activities like mowing or understory clearing that would prevent natural regeneration (U.S. Forest Service 2007).

FIA produces estimates of several forest parameters and creates statistical and analytical reports that are used by many stakeholders, including local, state, national, and international scientists, land managers, and other decision makers (Gillespie 1999). For example, in order to fulfill mandates set out by the Forest and Rangeland Renewable Resources Planning Act of 1974 (RPA), FIA provides data and analyses to the national RPA assessment that is conducted periodically (U.S. Forest Service 2000; Smith et al. 2004). Other products include each state's annual and 5-year comprehensive analytical report (e.g., Piva et al. 2009a, b).

FIA data have often been applied to nontraditional forestry assessments like those required by the agroforestry community (Perry et al. 2008), forest health community (Krist et al. 2007), forest carbon inventories (Chen et al. 2011) and vegetation classification studies (Franklin 2002). However, because tree data are not collected in areas that do not meet the FIA definition of forest, it is difficult to apply FIA's tree data results to areas with little or no forest land use. FIA does produce estimates of the total area by land use (Smith et al. 2004), but tree data within the nonforest areas are completely lacking.

The Great Plains states of North Dakota, South Dakota, Nebraska, and Kansas (hereafter referred to as the Plains States) are approximately 97% nonforest (Smith et al. 2004), and consist mostly of agricultural and grassland vegetation communities. Plains State resource agencies have recognized the lack of available information on the nonforest tree (NFT) resource and how this knowledge gap might hinder wise management of these areas. The US Forest Service periodically conducts assessments of forest health in the Plains States and has identified a number of forest health concerns, including flood damage, ice storms, invasive species encroachment, and various insect and other plant diseases (U.S. Forest Service 2009a, b, c, d). Of particular concern is the spread of the emerald ash borer (EAB) (*Agrilus planipennis* Fairmaire), which, since being identified in 2002 near Detroit, Michigan, has been found in Illinois, Indiana, Kentucky, Maryland, Minnesota, Missouri, Ohio, Pennsylvania, and Wisconsin, and as far north as Quebec and Ontario Canada. Although EAB has yet to be confirmed in the Plains States (as of January 2010), this region has some of the greatest relative density (percent of the total basal area) of EAB hosts (*Fraxinus* spp.), with mostly green ash (*Fraxinus pennsylvanica* Marsh.) found along riparian areas, in conservation tree plantings, and as a common tree in the communities across the plains (Fig. 1). Hansen and Hoffman (1988) report that green ash is a significant component of the vegetation in the northern Plains States. Ball et al. (2007) showed that ash is the most commonly planted street tree in South Dakota. Poland and McCullough (2006) identified potential ecological impacts of damage to the ash resource, including loss of cover and mast for wildlife, thermal effects, and soil erosion. In addition to the ecological effects they report, economic impacts, which nationally could run into the billions of dollars, include costs of removal, replanting, and control efforts.

In response to these concerns, state forestry agencies in the Plains States, with funding assistance from the US Forest Service's State and Private Forestry group, are assessing the potential economic and ecological impacts of EAB-induced ash mortality. This project, called the Great Plains Tree and Forest Invasives Initiative (GPI), has several objectives, including a characterization of the existing NFT resource, the identification of mitigation needs and utilization opportunities, and the development of educational materials to help land managers and land owners cope with potential impacts (Nebraska Forest Service

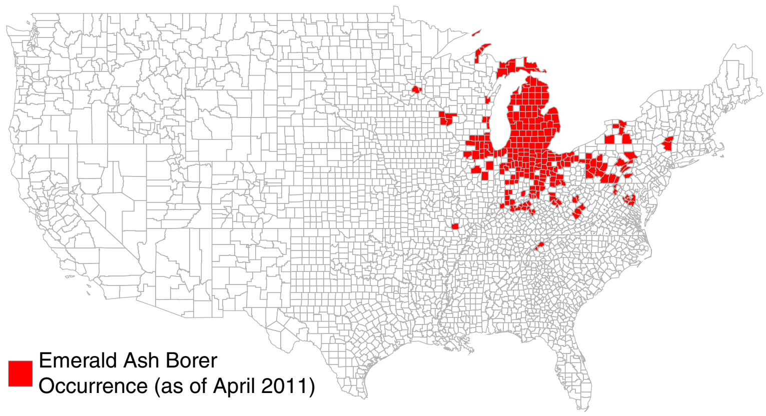

Fig. 1 Map of US counties with occurrence of emerald ash borer as of April 2011

2007). To meet the first objective, FIA's National Inventory and Monitoring Applications Center (NIMAC) helped design the inventory, process the data, and create a reporting tool to provide information that will characterize the NFT resource and supplement the information that FIA collects on the tree resource in forested areas.

The goals of the inventory included obtaining state-level estimates of NFT parameters, including area of land with different classes of NFT land use and estimates of total amounts of several continuous variables (e.g., area estimates by the primary function [benefit] the windbreaks provide, volume, and tree counts by species or genus grouping). An additional component of the inventory, not reported here, focused on NFTs in urban areas, with results serving as input to the Urban Forests Effects (UFORE) model, which, among other things, assigns estimates of value to urban forest components (Nowak and Crane 2000). This paper describes how NIMAC extends traditional FIA plot and sample design methodology to the nontraditional Plains States NFT inventory.

Methods

NIMAC and Plains States forestry officials undertook a planning process that identified desired outcomes, precision requirements of NFT parameter estimates, existing FIA data sources, and new variables that were required to meet goals. The result of this process was the choice of a plot design that represents a tradeoff between a desire for compatibility with FIA methodology and cost effectiveness in the field. The field plot consisted of a single, 0.067-ha circular plot on which a variety of FIA, UFORE, and other site and tree-level attributes were recorded (Table 1). A single plot was chosen over the FIA four-subplot design (U.S. Forest Service 2007) to enhance field efficiency—the objective was for the field crews, which had varying levels of experience, to have minimal set-up time for each plot relative to the reduced set of information recorded on trees. The FIA field guide, data recorder software program, and database storage system were adapted to accommodate the Plains States variables.

Field crew training was coordinated with state forestry and FIA staff using the GPI inventory field guide (available upon request from the authors) we developed. In 2008, field crews were hourly summer employees supervised by state forestry personnel in Kansas, Nebraska, and South Dakota; North Dakota used existing state forestry staff. Most of the data collection occurred between mid-May and the end of August. Each two-person crew visited 100–150 plots. In 2009, the same approach was used in Kansas, Nebraska, and North Dakota; South Dakota elected to employ a consulting forestry team to measure their 200 plots. Crews were able to collect data on between one and four plots per day.

Tree data were only collected on plots that had trees that were not in what FIA defines as a forested condition. "Conditions" are portions of plots that are akin to landscape patches, and are delineated using criteria related to land-use type,

Table 1 A listing of the attribute data collected on the GPI plots

Type	Attribute	Plot type
Plot	GPS coordinates	U,R
Plot	Rural or urban plot	U,R
Condition	Primary land use[a]	U,R
Condition	Windbreak width (3-m increments)	R
Condition	Windbreak condition[b]	R
Condition	Windbreak age	R
Condition	Planted vs. natural	U,R
Condition	Function of trees[c]	R
Condition	NFT land use present/absent	R
Condition	Canopy cover class	U
Condition	Owner group (private or federal/state/local)	U,R
Tree	Species	U,R
Tree	Diameter (2.54-cm increments)	U,R
Tree	Height to location of diameter measurement	U,R
Tree	Height to base of the live crown (1.5-m increments)	U
Tree	Height to top of tree (1.5-m increments)	U,R
Tree	Crown dimensions—perpendicular axis lengths (1.5-m increments)	U
Tree	Foliage present/absent	U
Tree	Crown light exposure class	U
Tree	Crown dieback class	U,R
Tree	Distance and azimuth to 3 nearest buildings	U,R

On each plot, different types of data were collected. Plot data characterize the entire plot area. Condition data characterize contiguous areas that are formed using land use delineation rules. Tree level data are those collected on trees not found in conditions that would be classified by FIA as forest

U urban, *R* rural

[a]This attribute consists of 17 anthropic and natural classes and include inaccessible and denied access areas

[b]Good, fair, or poor, based on criteria including % live trees, windbreak completeness, density of trees, presence of invasives, evidence of diseases, presence of regeneration, and expected longevity

[c]Tree planting functions include farmstead, field or livestock windbreak, living snowfence, home acreage planting, wildlife habitat planting, abandoned farmstead, planted riparian buffer, natural riparian forest buffer, or narrow wooded strip

ownership, and certain forest compositional and structural attributes (U.S. Forest Service 2008). The plot center and each tree were assigned one of the condition-level attributes (Table 1). This allows not only for the production of estimates of the total area of each of the condition variables, but also for the use of these variables for grouping and thus partitioning the estimates into domains (categories). For example, one could generate estimates of the total area of each owner group, and the number of trees by owner group.

Figure 2 depicts the process for establishing and conducting the inventory. An assessment of the field data collection budget for the summer

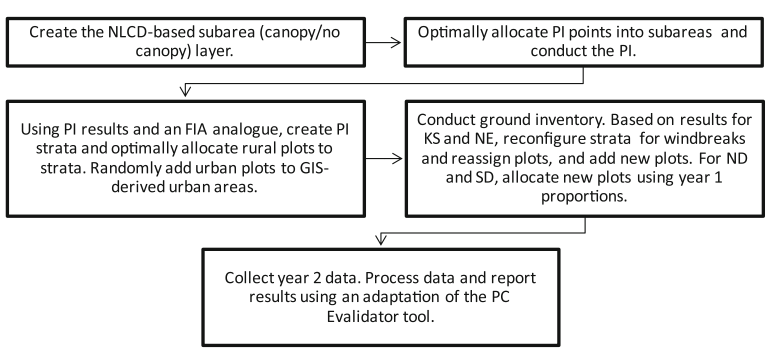

Fig. 2 A flow chart of the GPI inventory design process

months of 2008 (first year of data collection) revealed that in each state 100 rural plots and 200 urban plots could be measured with the existing funding, which was divided equally among the states. For the urban areas, which had a different sample design and intensity due to the needs of the UFORE project, a GIS file representing urban area boundaries was derived from the US Census Bureau's Tiger Line Files (U.S. Census Bureau 2002), and individual state cooperators reviewed the list of resulting urban areas in order to eliminate areas that did not meet the definition of "urban" they chose for the project. From the resulting list, plots were randomly chosen from the set of urban area polygons using a GIS-based random point generation procedure. Within a state, all urban areas were thus treated as a single estimation unit, with larger urban areas being more likely to contain more plots.

For rural areas, the small number of plots compounded the concern that the attributes of interest, which are associated with NFT land use, are only represented in about 1% of the overall land area of the four states based on estimates from a photointerpretation (PI) that FIA does in support of its ground inventory. In situations where there is potential to collect less costly information on a large number of elements in the population and to collect more costly, direct measurements of the attribute of interest on a subset, multi-phase sampling is suggested (Cochran 1977). For example, Holmgren et al. (1994) performed a study in which multi-phase sampling was found to be effective at characterizing the NFT resource in Africa. We chose a stratified, two-phase sample design for the NFT survey of the rural areas of the Plains States.

The first step in the process was to partition each state into two subareas (canopy and no canopy) using a derivative of the National Land Cover Dataset (NLCD). NLCD is a set of satellite image-based products produced by a consortium of federal agencies, led by the US Geological Survey (Homer et al. 2007). These products are comprised of 30-m pixels, each labeled with a land-cover category, percent impervious surface, and percent canopy cover estimates. To create the subareas, a "focal" spatial filtering approach, which is akin to a low-pass filter, was applied to the percent canopy cover map. For each 3 × 3 block of pixels in the image (the focal window), the count of pixels with any estimated canopy cover in them was assigned to the center pixel of the block. The focal window was then shifted over one pixel, the count summarization was repeated, and the process was repeated for each pixel in the image. This resulted in an image containing pixel values of 0 (no canopy cover in the focal window) to 9 (all nine input pixels contained canopy cover). This image was then recoded into the final subarea map: values of 0 were assigned to subarea 1, and all other values were assigned to subarea 2 (Fig. 3). For the four-state area, approximately 90% of the area fell into subarea 1, which we considered more likely to be devoid of trees.

The next step was to select elements within each subarea for the first phase of the two-phase sample. Phase 1 consisted of a large number of PI plots overlaid on circa 2006 National Aerial Imagery Program (NAIP) imagery, with a different intensity in each subarea. Each PI plot consisted of 21 uniformly spaced points located within the footprint of potential ground plots—a 0.067-ha circle. Twenty-one points were chosen based on prior experience and a tradeoff between time cost per plot and completeness of area coverage for NFT assessment. The land use (using FIA definitions [U.S. Forest Service 2007]) of each of

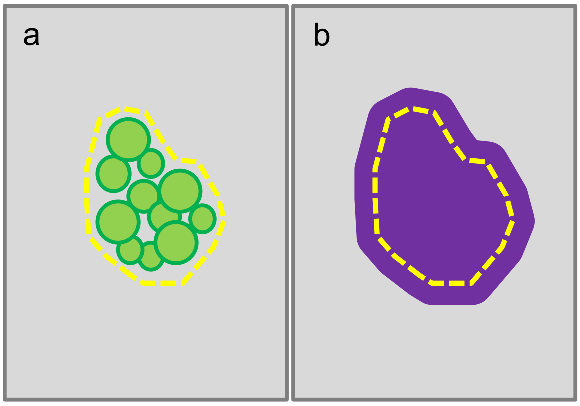

Fig. 3 **a** A depiction of the original extent of the binary-coded NLCD canopy map—the area within the *dotted boundary* was labeled as containing tree canopy. **b** The original canopy area, and the shaded area that extends beyond the original extent of canopy, produced by a spatial filtering method. The *dark, shaded area* represents subarea 2 (canopy) on the image, and the remaining area represents subarea 1 (no canopy)

the 21 points was assessed and the count of points falling in the NFT land use category was recorded for each PI plot.

Based on consultation with PI specialists and a pilot assessment of the PI methodology, it was determined that the project budget allowed for 18,000 PI plots to be completed for each state. We chose the proportion of these 18,000 plots per subarea per state using optimal (Neyman) allocation to minimize the variance of estimates given the number of PI and ground samples available (Cochran 1977). To determine these optima, existing FIA ground plots were first assigned a subarea by intersecting them with the subarea map in a GIS. The variance of the binary-coded land use category (NFT/other) of the center of the FIA plot was then calculated for each subarea. These variances were used to optimally allocate PI plots to each subarea.

Within each of these subareas, the phase 1 samples were assigned values of 0–21 via PI based on the potential NFT land-use count. Phase 2 of the two-phase sample was established by optimally choosing ground plots from within phase 1 strata created from these PI results in a spatially balanced manner (Lister and Scott 2008). To create the phase 1 strata, stratum breakpoints were established across the range of PI values (0–21). The stratum breakpoints were chosen using FIA plot data as an analogue, taking advantage of the "percent forest" value assigned by field crews to each FIA plot. We assumed that the percent forest estimate on FIA plots is analogous to the proportion (out of 21) NFT land use assigned to a PI plot. Using that assumption, we heuristically assessed how collapsing the FIA percent forest value into various configurations of three strata served to lower the variance of estimates of total number of trees and cubic foot volume from the FIA plots. This stratum creation procedure was iteratively performed with different break points, looking for configurations that led to having at least ten GPI plots per stratum, and to the most variance reduction of estimates of both FIA attributes.

Once we arrived at a stratum configuration that generally met these criteria in each state, we translated the stratum boundaries from the FIA percent forest scale (0–100% forest land use) to PI plot scale (0–21 NFT points/plot). This yielded at most three strata, which we defined as "no trees", "low trees", and "high trees", based on the number of NFT PI points found on the plot. We then used the resulting PI plot stratum boundaries, associated stratum areas, and FIA attribute variance estimates to optimally allocate GPI ground plots (phase 2) into each stratum. No ground plots were sampled in the first stratum of each subarea (the "no trees" stratum, which had 0 NFT points). These strata were assumed to have no NFT because of the high quality of the imagery and the cost of sampling the stratum.

To assess the relationship between the expected sampling error (from the FIA plots) and that obtained by stratifying the GPI plots using the FIA-based stratum boundaries, we calculated diagnostic statistics (slope, y-intercept, and coefficient of determination) of a simple linear regression line describing the relationship between the sampling errors for estimates of total numbers of trees for each estimation unit.

Due to an increased interest in the status of windbreaks in Kansas and Nebraska, a reconfiguration of the phase 1 strata was performed prior to allocating plots for year 2. We accomplished this by reinterpreting each PI plot that had any NFT measured on them during phase 1 (i.e., the low and high trees strata) and relabeling them with the GPI land use category (Table 1). For each subarea, the original set of strata in each of these states were then reconfigured using this new information into strata defined as "no trees" ,"low trees", "low trees with windbreaks", "high trees", and "high trees with windbreaks". The existing plots were reassigned to these strata. New plots (173 in Nebraska and 190 in Kansas) then were allocated to these new strata based on the proportion of the phase 1 plots within the two windbreak strata. For North Dakota, 100 plots were randomly added to the urban areas and 50 plots were added across all strata of the rural areas using the year 1 proportions. In South Dakota, 200 new plots were added across the rural subareas and strata using the year 1 proportions as well.

Data collection ended during the fall of 2009. Data were processed, stored in an Oracle database and inserted in an adaptation of FIA's PC EVALIDator reporting tool (Miles 2009) for reporting. EVALIDator is a Microsoft Access database that stores data and generates reports using a combination of innate Access functionality and Microsoft Visual Basic for Applications scripting. It is designed to use files that are based on the FIADB, FIA's publicly accessible database (U.S. Forest Service 2008). Double sampling estimation equations used by our modified version of EVALIDator follow those presented in Cochran (1977). For urban areas, which were treated as separate estimation units, simple random sample estimates were generated, allowing state-level totals to be formed by combining estimates from the rural and urban estimation units.

Results and discussion

A total of 36 state–subarea–stratum combinations were used. An example of counts of plots per subarea and stratum for 2008–2009 data are shown in Table 2 for South Dakota; the other states show similar patterns. The optimal allocation of PI points clearly shifts points into subarea 2 due to the higher variance of FIA plot values (not shown) that occurred in this area (it contains only 8% of area, but 30% of the plots). Subarea 1 areas are those with no nearby canopy predicted by NLCD. Generally, for an FIA plot to fall in this area, either its classification as forest is anomalous (for example, a clearcut) or the area's tree canopy signal is weak—its composition or configuration is such that it confounded the NLCD canopy prediction algorithm. From inspection of the NLCD and NAIP imagery, we found that subarea 2 (areas on or immediately next to pixels classified by NLCD as containing tree canopy) generally had a strong canopy signal—generally, a significant number of well-defined tree canopies. Since this area had most of the NFT resource, then it also had much of the variability, and thus affected the optimal allocation outcomes as shown.

Table 2 An example of the count of PI point and plot count for each subarea-stratum combination

South Dakota	0–21 splits	Area (%)	PI plots	Ground plots
Subarea 1		91.5	12,582	183
No tree	0		12,316	0
Low tree	1–6		151	69
High tree	7–21		115	114
Subarea 2		8.0	5,478	117
No tree	0		4,868	0
Low tree	1–8		328	48
High tree	9–21		282	69
Urban	N/A	0.5	N/A	200

The 0–21 splits, or stratum boundaries, were chosen based on boundaries obtained from an analogous FIA dataset

We chose an innovative strategy for creating strata from the PI results and allocating ground plots out of necessity—we had no ground data with which to estimate variance, create strata, and weight the allocation. We assumed that the relationship between the variance of attribute estimates from plots grouped by FIA percent forest was analogous to that we would obtain in NFT areas by grouping based on percent NFT measurements from the PI. We adopted our assumption that using an FIA analogue was likely a reasonable strategy because both FIA forest and NFT land encompass a broad range of tree densities, and thus the relative locations of stratum boundaries from NFT data should parallel those from FIA data.

The set of rural strata exhibited a wide range of percentages of ground plots that contained NFT land. For example, the percentage of plots per stratum that had NFT land use on them ranged from 32% (the low tree stratum in North Dakota) to 91% (the high tree stratum in Kansas), with a median of 76%. As expected, median percentages of ground plots with trees were higher in the high tree (80%) compared to the low tree strata (67%). The less-than-perfect correspondence between field and PI identification of the NFT resource was expected and somewhat desirable—the PI staff was instructed to err on the side of labeling an area as NFT if there was ambiguity, ensuring that few true NFT areas would not be considered for inclusion in the field survey. In urban areas, there was a much lower median percentage (46%); this low number was due to the fact that urban plots were located at random, with no attempt to prestratify.

Figure 4 depicts the relationship between the sampling errors of stratum-level tree density estimates expected from the FIA plots using the FIA boundaries and those observed from the GPI data.

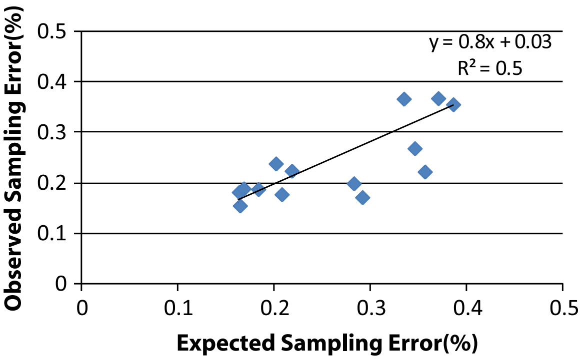

Fig. 4 Relationship between observed (from the GPI survey) and expected (from analogous FIA data) sampling errors. The FIA analogue was used to determine stratum boundaries. Resulting variances were highly correlated with those expected from FIA

The relationship is nearly 1:1 and the intercept of a simple linear regression line that characterizes the relationship is nearly zero. Although there is significant scatter about the line, the strong positive correlation suggests that our use of the FIA information as a pilot dataset with which to optimize stratum assignments had merit. FIA data are being used in this manner for planning purposes in the US Forest Service's National Forest System (Scott 2009).

One example of output from our modified EVALIDator program is that the number of ash trees in the nonforest portion of the states falls between 34% (in Nebraska) and 104% (in South Dakota) of that in the forested portion (Table 3). This is not surprising because ash trees are often planted in wind breaks and around structures, and are relatively well suited to the environmental conditions found in these states. Information like this, which our EVALIDator reporting tool can produce via a series of simple, menu-based queries, will help Plains State stakeholders learn more about tree species composition, species–environment relationships, and the potential impacts of forest health threats like the EAB in these NFT areas.

Conclusions

We learned much from the process of planning and establishing the Plains States NFT inventory. The process of setting inventory goals and choosing variables to meet these goals was an iterative process. Frequent meetings with all interested parties, as well as establishment of expectations in light of the available budget, helped to ensure that the inventory would efficiently provide the answers to management questions.

Another finding was that PI of nearly 80,000 plots (1,680,000 individual points to assess) required a great deal of effort to develop an efficient procedure, construct a manual, and manage and train analysts. The task became more manageable after we developed a GIS procedure that vastly increased our productivity level and lowered costs. In addition, photointerpreting plots in the Plains States was less complex because the vast majority of the plots assessed were completely devoid of trees. The experience we gained in this work will speed up future photo studies we conduct.

Table 3 An example of results from the EVALIDator reporting tool—GPI estimates can be compared to those obtained from FIA data collected in forested areas

Inventory	State	No. ash		Total no.		Proportion
		Trees	SE (%)	Trees	SE (%)	ash
GPI	KS	14,306,127	65.77	178,756,851	9.63	0.08
	NE	11,820,328	20.07	119,220,902	8.02	0.10
	ND	34,427,005	18.66	85,011,866	11.27	0.40
	SD	24,305,031	12.85	74,737,613	7.84	0.33
	Total	84,858,491	14.20	457,727,232	4.95	0.19
FIA	KS	41,932,111	18.40	752,785,938	5.32	0.06
	NE	34,911,168	18.80	347,215,165	7.14	0.10
	ND	79,151,049	14.33	331,378,919	10.82	0.24
	SD	23,225,202	20.22	536,695,502	5.96	0.04
	Total	178,188,470	8.86	1,968,075,524	3.42	0.09

Finally, we learned that some of the existing FIA infrastructure, including the field guide, data recorder, and analytical software, is adaptable for other FIA-like resource inventories. By going through the process of adapting the FIA methodology to fit the NFT inventory, the project not only benefits from using pre-existing infrastructure, but also from the potential for integration of NFT results with those from FIA. That is, using methods that are consistent with FIA allowed for comparisons between forest and nonforest areas. Approaches we developed in this study will be used in future work to improve monitoring efforts within FIA and possibly other agencies.

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