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REVIEW

Applications of the United States Forest Inventory and Analysis dataset: a review and future directions

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Abstract: The United States Forest Inventory and Analysis (FIA) program has been monitoring national forest resources in the United States for over 80 years; presented here is a synthesis of research applications for FIA data. A review of over 180 publications that directly utilize FIA data is broken down into broad categories of application and further organized by methodologies and niche research areas. The FIA program provides the most comprehensive forest database currently available, with permanent plots distributed across all forested lands and ownerships in the United States and plot histories dating back to the early 1930s. While the data can be incredibly powerful, users need to understand the spatial resolution of ground-based plots and the nature of the FIA plot coordinate system must be applied correctly. As the need for accurate assessments of national forest resources continues to be a global priority, particularly related to carbon dynamics and climate impacts, such national forest inventories will continue to be an important source of information on the status of and trends in these ecosystems. The advantages and limitations of FIA's national forest inventory data are highlighted, and suggestions for further expansion of the FIA program are provided.

Key words: monitoring, carbon, planning, sampling, remote sensing.

Résumé : Le programme d'analyse et d'inventaire forestier (AIF) des États-Unis assure le suivi des ressources forestières aux États-Unis depuis plus de 80 ans. Nous présentons ici une synthèse des applications des données de l'AIF en recherche. Une revue de plus de 180 publications qui utilisent directement les données de l'AIF est subdivisée en grandes catégories d'applications et subséquemment organisée par méthodologies et créneaux de domaines de recherche. Le programme d'AIF fournit la plus complète base de données forestière couramment disponible, avec des placettes échantillons permanentes réparties à travers toutes les terres boisées et tenures aux États-Unis, ainsi que l'historique des placettes depuis le début des années 1930. Bien que les données puissent être incroyablement puissantes, les utilisateurs ont besoin de comprendre que la résolution spatiale des placettes échantillons sur le terrain et la nature du système de coordonnées des placettes de l'AIF doivent être appliquées correctement. Étant donné que l'évaluation exacte des ressources forestières nationales demeure globalement la priorité, particulièrement en lien avec la dynamique du carbone et les impacts du climat, de tels inventaires forestiers nationaux vont continuer à être une importante source d'information sur l'état et l'évolution de ces écosystèmes. Les avantages et limites des données d'inventaire forestier national de l'AIF sont soulignés et des suggestions pour l'expansion future du programme d'AIF sont présentées. [Traduit par la Rédaction]

Mots-clés : suivi, carbone, planification, échantillonnage, télédétection.

Introduction

National forest inventories (NFIs) are critical for generating national estimates of carbon stocks and fluxes, as well as for supporting long-term forest planning and product utilization. Carbon stocks in forest ecosystems comprise a large percentage of global carbon, and carbon sequestration in forests and forest products is important for the mitigation of net greenhouse gas emissions (Fahey et al. 2010). Regional-scale data are therefore needed to address large-scale questions about forest resources and carbon stocks and fluxes in these pools over time. Since the 1928 Forestry Research Act, the United States Forest Service (USFS) has been charged to "make and keep current a comprehensive inventory and analysis of the present and prospective conditions and requirements for the renewable resources of the forest and rangelands of the United States and cooperate with the appropriate officials of each State, territory, or possession of the United States." This charge makes the USFS responsible for not only inventorying forests in the continental United States, but also Hawaii, Alaska, and all forested territories, including Puerto Rico, the U.S. Virgin Islands, Guam, Palau, the Republic of the Marshall Islands, American Samoa, The Commonwealth of the Northern Marianas, and the Federated States of Micronesia. Early NFI efforts were conducted under the title "Forest Survey," ultimately renamed "Forest Inventory and Analysis" (FIA) to highlight use of

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the data and not just data collection. The FIA program has gone through numerous changes in protocol and design following internal agency and national policies (Fig. 1). Program management was originally organized under five separate regions, each with unique inventory protocols and frequencies, making data comparisons between regions difficult and unreliable. The United States 1998 Farm Bill included language mandating a unified NFI protocol that integrates the Forest Health Monitoring (FHM) program on a subset of FIA ground plots (Bechtold and Patterson 2005; McRoberts et al. 2005). This led to the current FIA sampling frame and plot design. The FIA program currently provides data to monitor carbon stocks and changes across all forest carbon pools and supports national and international reporting in the forest land category. In terms of spatial and temporal extent, the FIA program is one of the largest natural resource datasets globally (Gelfand et al. 2013). While there are other NFI programs that share many elements of design with FIA, and even a few utilizing higher sampling intensities such as in Finland, Italy, Germany, and France, none of the other large-scale NFIs match the range of ecological diversity that FIA must represent (Tomppo et al. 2010). The scope of the program has expanded since the 1930s, when it solely focused on assessing timber resources, to the present structure that includes additional variables to facilitate assessments of carbon, wildlife, forest health, insects and disease, and invasive species (Shaw 2008). Many of the studies evaluated in this synthesis couple FIA with other data such as laser altimetry data (Pflugmacher et al. 2008) or use statistical approaches to model multivariable forest composition and structure from remotely sensed data (Hudak et al. 2008; Brosofske et al. 2014). One distinct advantage of FIA over similar databases is that it has no geospatial bias as the plots are distributed evenly across the entire United States on all forest lands (Smith 2002). FIA data are publicly available for all United States forest lands, though the actual locations of these plots are protected (Shaw 2008). This synthesis extends a previous review by Rudis (2003) by evaluating research that has directly utilized FIA program data and makes recommendations for future uses.

This synthesis is organized thematically, with each subsection seeking to address the following three questions. (1) What subject areas can the data be effectively used for? (2) What analytical approaches are being used with the data? (3) What are the related challenges and opportunities of FIA data?

Review process

The objective is not to provide an exhaustive review of all literature relating to FIA, but rather to provide a synthesis highlighting the diversity of research and applications for FIA. This synthesis was achieved by searching for all publications containing the words forest, inventory, and analysis within Thomson ISI Web of Science (n = 336). These publications were then filtered for publications longer than four pages, this eliminated many proceedings, data summaries, and agency publications that were informational instead of research oriented (leaving n = 287).

This selected literature shows how the FIA program has grown in its research significance over the last three decades, with the number of publications per year increasing by ~0.90 research manuscripts per year since 1991 (Fig. 2). This increasing trend is attributed to the standardization of the FIA data collection process, the move to annual inventories, and advances in remote sensing and statistical analysis techniques. The remaining publications were evaluated for their ability to support the background of the FIA program, explicitly using FIA data within their analyses, and the novelty of the FIA data application to avoid redundancy (n = 195). Of this literature, a consistent proportion of the candidate literature was cited in this synthesis from each of the last three decades (Fig. 2). From this three-decade period, more than 50% of the publications using FIA data in their analysis have been

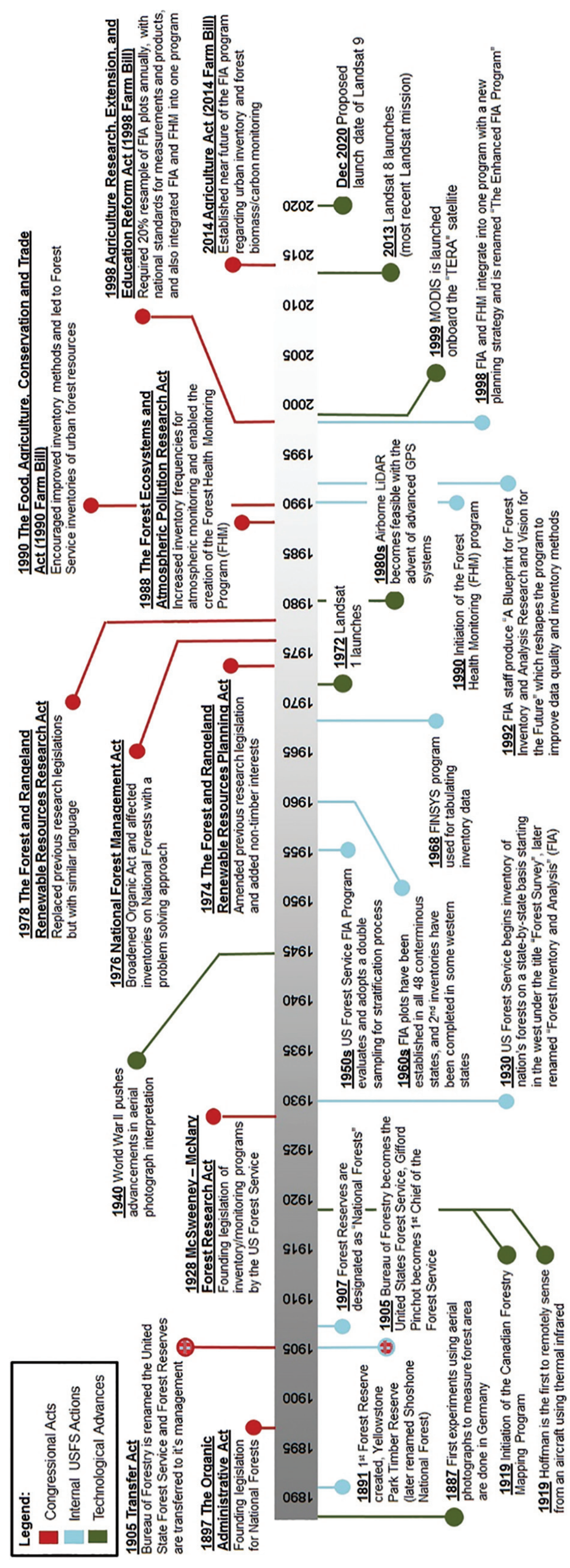


Fig. 1. Timeline of substantial FIA program changes through Congressional Acts, internal program changes, and technological advances, particularly remote sensing (Bechtold and Patterson 2005; Landsat 2016; Shaw 2008). [Colour version online.]

Fig. 2. Number of published papers by year identified for potential inclusion and number cited in the synthesis.

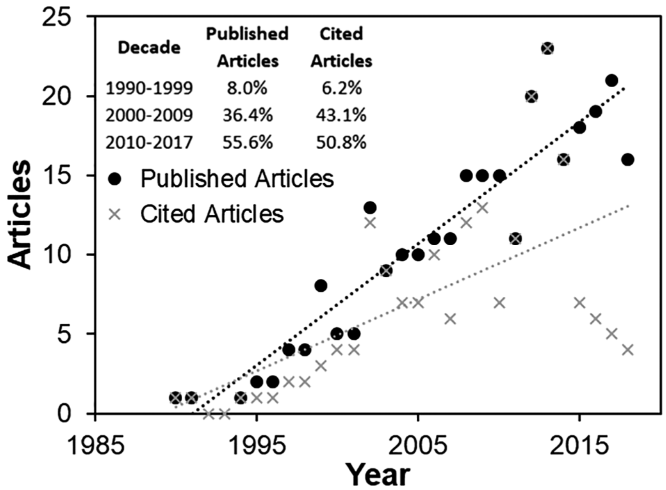


Table 1. Breakdown of cited literature by the section of occurred.

FIA data applications	No. of papers cited	Proportion (%)
Carbon cycle applications	45	23.1
Forest products and forest growth applications	27	13.8
Climate applications	15	7.7
Forest health applications	57	29.2
Remote sensing applications*	33	16.9
Introduction, design, and discussion sections	18	9.2
Total	194	100

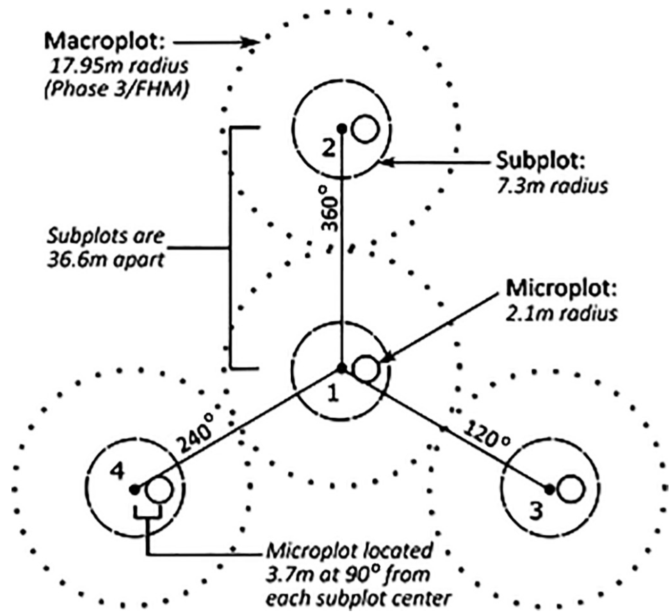
*May be underrepresented as articles were attributed to the first section in which they appeared.

related to forest health and carbon cycle applications (Table 1). Notably, some of these articles may have also been related to remote sensing applications, but these articles were attributed to the first section of the synthesis in which they appeared.

FIA sampling procedures

Detailed descriptions of the FIA sampling protocol have been widely described in the forestry literature (e.g., Bechtold and Patterson 2005; Shaw 2008; McRoberts et al. 2005; Hoffman et al. 2014), thus only a brief description follows. The FIA program conducts inventories in multiple phases and uses stratified estimation to estimate population parameters for most variables (McRoberts and Miles 2016). In Phase 1, remotely sensed products are used in a pre-field process to stratify the population area to reduce the variance of estimates by determining land use (e.g., forest land or cropland) at all plot locations. In Phase 2, which is a subsample of the initial phase, permanent ground plots are randomly distributed without regard to land cover, land use, ownership, or other factors, approximately every 2428 ha across the 48 conterminous states of the United States. The intensity of sampling is reduced within Alaska and increased within some United States territories. If any portion of a plot is determined to contain a forest land use, it is measured by a field crew. Forest land plots provide the basis for all summaries and products available from FIA and are freely accessible from the FIA program (FIA DataMart 2018, https://apps.fs.usda.gov/fia/datamart/datamart.html, accessed 11 October 2018). While the original intent of the FIA sampling design was to provide broad-scale estimates of forest statistics, it is increasingly common for users to directly utilize the field plot observations.

Fig. 3. Current FIA plot layout.



To preserve the ecological integrity of plot locations, protect proprietary information (e.g., plots on privately owned land), and provide unbiased forest resource information, the FIA program has established a policy of not disclosing exact plot locations (McRoberts et al. 2005). Publicly available coordinates are truncated (sometimes referred to as “fuzzed”) to be within roughly 1 km of the actual plot location, and up to 20% of the plots on private land in each county have their coordinates swapped to further obscure their true location (Gibson et al. 2014). Thus, the highest spatial resolution to which public FIA data can be resolved is the county, where in some cases, particularly in the eastern United States, small counties are aggregated to obtain desired precision standards. Therefore, while FIA plots have a spatial distribution of one plot for every 2428 ha in the continuous 48 states, the resolution of summarized data is not spatially explicit, as each county has a different area. An exception occurs when single plots are tracked over successive inventories, as the location does not change once a plot is established. By United States federal law, the confidentiality of true plot locations must always be maintained in use of FIA data and therefore may not be published.

Each permanent ground plot comprises four subplots arranged in a cluster, with one plot in the center and three plots arranged radially 36.6 m from the center plot at azimuths of 0°, 120°, and 240° (Fig. 3). All permanent ground plots with at least one forest land condition (i.e., domains mapped on each plot using land use, forest type, stand size, ownership, tree density, stand origin, and (or) disturbance history — there may be multiple conditions on a single inventory plot; Bechtold and Patterson 2005) are remeasured every 10 years in the west and every 5–7 years in the east, resulting in a 10%–20% sample annually. Each subplot has a 7.3 m radius, and all live and standing dead trees over 12.7 cm diameter at breast height (DBH) are inventoried. Within each subplot, there is a 2.1 m radius microplot 90° from plot center. Live saplings and seedlings are recorded within each microplot. Each subplot is nested within a 17.95 m radius macroplot on which additional attributes are measured on intensive plots. The macroplot is also used in some regions to capture rare occurrences such as large trees and mortality, which would otherwise be missed due to the rare event phenomenon (Bechtold and Patterson 2005). Additionally, on 5%–15% of ground plots, additional site-level (e.g., litter and soil) and tree-level (e.g., crown condition) variables are measured in what are referred to as FHM plots or Phase 3 of the design (Bechtold and Patterson 2005; Shaw 2008; Domke et al. 2017).

Carbon cycle applications

Assessment of carbon pools, sequestration rates, and trading each rely on estimates of forest biomass as a proxy for forest carbon. Within the ground-based plots of Phase 2, commonly used forest inventory variables (i.e., DBH, total height, and crown base height) for biomass assessment through allometric relationships are collected. These variables and the FIA sampling strategy lend themselves to both plot- and county-level summarization through the FIA database (FIA DataMart 2018, https://apps.fs.usda.gov/fia/datamart/datamart.html, accessed 11 October 2018) and its associated tools (e.g., EVALIDator) for generating biomass summaries. The standardization and temporal continuity of the FIA database make it uniquely suited for assessing trends in biomass levels, which can be directly and empirically linked to storage and fluctuations in elements such as carbon and nitrogen in trees through previously established allometry. When augmented by Phase 3's additional measurements of parameters such downed woody material (DWM), soil chemistry, and understory plant composition, these observations can be used to look at things such as ecosystem-level carbon pools and fluxes. Although studies using FIA data for carbon cycle applications have broadly varied in their scale, nearly all have focused on one of four applications: (1) direct observation or assessment of change, (2) calibration or training of a model, (3) validation of model outputs, or (4) a combination of calibration and validation.

Many studies have used FIA data to look at either static snapshots of carbon and nitrogen pools or their fluctuations through repeated measurement cycles. For example, Goodale et al. (2002) used net annual growth and age-class structure data from the FIA database to estimate the amount of nitrogen sequestered annually by forests in 16 large watersheds across the northeastern United States. Using a similar approach, Hu and Wang (2008) tracked carbon sequestration over a 70-year period in the Piedmont forest in South Carolina. In terms of aboveground biomass and carbon, Brown et al. (1997) used FIA data to estimate the difference in biomass between old growth (>70 cm DBH) and sawtimber forest types, while Gray et al. (2014) took this a step further and used successive FIA inventories to track changes in carbon flux from aboveground biomass change and linked the changes in biomass to different causes. In more targeted efforts, several studies have used FIA data to estimate standing dead trees and DWM, along with the carbon stocks and dynamics associated with DWM in forest ecosystems (Chojnacky and Heath 2002; Chojnacky and Schuler 2004; Woodall et al. 2008, 2012*a*, 2012*b*, 2015; Domke et al. 2013*a*). Specifically, Chojnacky and Schuler (2004) used FIA to estimate biomass in DWM per acre for mixed-oak forests in four states in the eastern United States, noting that while FIA provided an adequate per acre summary, the resolution is coarse due to the nature of the database. More recently, Hoover and Smith (2012) utilized FIA site productivity condition class indicators to provide broad guidance about the use of different forest types in carbon offset projects. The study found that all but the lowest quality and lowest productivity have potential as forestry-based greenhouse gas mitigation projects.

Taking the use of the data a step further, many studies have combined FIA data with other datasets to develop and calibrate models of forest biomass and carbon stocks. Building on some of their earlier work, Brown and Schroeder (1999) used FIA data to map annual aboveground biomass flux at a county level across the eastern United States. In a similar effort by Jenkins et al. (2001) focused on mapping biomass stocks, plot-level FIA data were rescaled from the county-level resolution of publicly available FIA summaries to a half-degree resolution for the entire mid-Atlantic region. He et al. (2012) developed complete carbon budgets for different forest types based on age by utilizing aboveground NPP from FIA data and estimates of belowground NPP from remotely sensed maps of leaf area index. Taking model development to a finer spatial scale, Williams et al. (2012) used FIA data to examine relationships between aboveground biomass fluctuations and stand age, as it related to disturbance and recovery cycles. In a more specific study, Chojnacky and Heath (2002) used Phase 3 plots to explore the relationship of DWM to other plot variables measured by FIA to identify which had the most predictive power in Maine forests. Dead standing trees and stumps proved to have the most predictive power for estimating DWM, each of which are standard measurements in Phase 2 of the FIA system, while live tree variables showed almost no relation to DWM. In an effort to model carbon fluctuations, Nunery and Keeton (2010) used FIA as a source dataset for FVS estimations of aboveground biomass under different management regimes over a 160-year period. In a more direct use of FIA to model carbon fluctuations, Gan and Smith (2006) estimated biomass residues from harvesting and their potential use in bioenergy production, but excluded losses due to silvicultural treatments. Taking this a step further, Perez-Verdin et al. (2009) used FIA data to estimate biomass volumes in Mississippi for use in bioethanol conversion. The most complete look at the influence of management and disturbance on carbon stocks came from Bradford et al. (2013), who used FIA data to model the influence of natural disturbance rates and harvesting on carbon dynamics on the Superior National Forest; they found that regional harvest projections continued to increase total terrestrial carbon stores, but that the projected increases in disturbance frequency due to climate change would have a long-term negative impact.

The next class of studies used FIA data to validate either local FIA summaries or outputs from another model. In terms of validation of the FIA system, Karlik and Chojnacky (2014) destructively sampled blue oak (*Quercus douglasii* Hook. & Arn.) in California to develop models of total biomass and biomass carbon, finding that the results compared well with biomass summaries for blue oak from FIA. In a similar study, Sabatia et al. (2013) used FIA to validate local allometric biomass estimates of eight FIA plots in southern Appalachian hardwood forests, demonstrating that local estimates were generally significantly higher than biomass estimates taken directly from FIA data, but they could not discern the reason for these differences. There are also a number of efforts that have used FIA data to validate other modeling platforms. Cartus et al. (2012) utilized FIA aboveground biomass summaries at multiple scales to validate remotely sensed biomass estimates from the Advanced Land Observing Satellite (ALOS) 30 m pixels to county scales. This study demonstrated that the ALOS estimates were more strongly correlated with FIA biomass summaries when pixels were aggregated to >500 m pixels. Hudiburg et al. (2013) improved the model form of the Community Land Model through FIA statistical training of the model's net primary production (NPP) equations. The study improved estimated precisions for stem biomass and NPP by 50% and 30%, respectively, by incorporating more variables based on physiological tree characteristics. Lichstein et al. (2014) improved large-scale aboveground biomass models by accounting for wider margins of error in parameter data. FIA data were used to explore how assumptions on data errors in climate and soil variables affect modeled estimates of biomass. FIA plot data were used to validate biomass estimates modeled under assumptions of very small error and very large errors. FIA data have long served as the foundation for estimates of carbon stocks and stock changes on forest land for the National Inventory Report of greenhouse gas emissions and removals in the United States submitted each year to the United Nations Framework Convention on Climate Change (U.S. Environmental Protection Agency (EPA) 2016). An early effort by Wilson et al. (2013) attempted to look at how nearest neighbor imputation routines could be trained by the FIA dataset for carbon project planning and reporting but determined that refinement in the modeling process was necessary to be useful at the project level. Domke et al. (2016) developed a modeling framework to estimate litter carbon stocks and stock changes on forest land from Phase 3 FIA plot attributes and auxiliary climate variables. When compared against a coarser national model of litter carbon stocks, their field-based approach showed a 44% reduction, suggesting a gross overestimation of the national model.

The final set of studies use FIA data in a more intricate way to either develop and validate the same model or to develop and then validate another model. Building on their earlier work, Domke et al. (2017) develop a model of litter carbon stocks and their changes from FIA Phase 3 inventory and biophysical attributes that they applied to all Phase 2 locations in a nonparametric modeling framework. This approach of using site-specific information yielded a 75% increase over State Soil Geographic Database estimates, demonstrating a substantial increase in the importance of soil carbon in total forest carbon budgets. When looking more broadly at aboveground biomass, Mickler et al. (2002*a*) linked biomass fluxes to different forest types and regionally modeled net primary productivity (Mickler et al. 2002*b*), with a focus on fire risk. Westfall et al. (2013) did a detailed assessment of aboveground biomass fluxes in the Great Lakes region using FIA data and found no net change in the carbon pool. Losses in biomass from reduction of DWM were balanced by gains in biomass from the growth of live woody plants, making the net carbon flux indistinguishable from zero by standard FIA summaries. Chojnacky et al. (2014) developed updated biomass models using individual-tree data from FIA and compared the results of individual-tree modeling back to generalized FIA biomass summaries. They found that, on average, FIA biomass summaries were 20% lower than biomass estimates produced from individual-tree modeling. Nay and Bormann (2014) developed site-specific biomass models for Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) in a single stand in the Siskiyou Mountains of southern Oregon. Biomass models were developed from 32 trees in the selected stand, and the results were compared with general regional and FIA models, respectively. The FIA-based models outperformed the regional biomass models that each led to a higher bias. MacLean et al. (2014) compared FIA estimations of aboveground biomass carbon to estimations from three different Forest Vegetation Simulator runs under different parameters: two calibrated tests and one uncalibrated test. Results showed little similarity between any of the biomass estimations, the point of the study being that we as scientists must be very careful about correctly calibrating models and using consistent inventory methods.

Similar studies have used FIA data in efforts to validate remote sensing products. For example, Li et al. (2009) coupled FIA data and Landsat TM data to improve the accuracy of remotely sensed forest types. Zheng et al. (2007) attempted to resolve the resolution issues between FIA estimates and MODIS-derived biomass estimates using empirical models developed from Landsat data. MODIS provides higher spatial resolution (500 m) than FIA data and synoptic coverage; hence, the combined product provides more spatially detailed biomass estimations for each forest type in the Lake States. Kellndorfer et al. (2006) used FIA biomass data to train and validate model projections derived using data from the Shuttle Radar Topography Mission of dry biomass and forest canopy height in Utah as part of a larger scale project to develop a nationwide model for mapping biomass, carbon, and canopy heights across the entire United States. Several studies have evaluated biomass fluctuations from disturbance events using FIA and remote sensing products. Chen et al. (2011) used FIA, Landsat, and LANDFIRE data to map aboveground biomass carbon and biomass loss due to fire. FIA data were used to train a regression model and then additional data were used to validate the output of that model. By combining FIA with the higher resolution data from Landsat and LANDFIRE, Chen et al. (2011) produced maps at a 30 m resolution. Williams et al. (2014) used Landsat imagery to estimate areas of disturbance and then stratified those disturbed areas with FIA data; stand age was used to constrain a carbon model to quantify the effect of stand age on biomass carbon fluxes. Sheridan et al. (2015) integrated LiDAR with FIA data to explore the ability of such systems to improve FIA biomass estimates at varying scales. The results demonstrated that LiDAR could reliably estimate biomass per FIA protocols and that potential existed to integrate LiDAR into standard FIA data collection procedures.

Schroeder et al. (1997) developed expansion factors for temperate broadleaf forests in the United States to convert timber volume to aboveground biomass carbon, highlighting a limitation in FIA summaries because they were based on merchantable timber volumes and did not include branches, foliage, etc. When compared with FIA-derived biomass, the predictions from Schroeder et al. (1997) produced predictably higher carbon estimates. For more accurate total biomass estimation, it is important to include all parts of the tree, not just the merchantable volume. This critique was addressed in the FIA program by adopting a component ratio method of biomass estimation, which provides separate estimates for each part of the tree (Woodall et al. 2011). Domke et al. (2012*a*) showed that the recently adopted component ratio method produced lower estimates of biomass than those previously produced, but speculation is that that these new estimates are more accurate because they incorporate tree height data by species and more locally derived components. The resulting changes in biomass estimations nationwide impact not only the FIA database, but also related programs such as the National Greenhouse Gas Inventory.

It is understood that long-lived old-growth trees can contribute a large percentage to total carbon sequestration, but it has been shown by Roesch and Van Deusen (2010) that the low plot density implicit within the sampling design of FIA misses a large percentage of large-diameter trees in three-quarters of the sampling regions. To overcome this issue, the Pacific Northwest Region of the FIA program implemented an additional protocol to capture rare large trees with high accuracy, highlighting that a similar protocol could be applied nationally to capture other rare conditions of interest.

Forest products and forest growth applications

One of the primary objectives behind NFIs is to track forest products and forest growth rates in support of sustainable forest management planning. Consistent, repeat measurements at the same sampling locations and inclusion of measurements beyond minimal inventory standards such as age and diameter growth increments from tree increment cores make FIA data useful for tracking forest products and growth. Although the number of studies using FIA data to assess forest products and growth are numerous, most of them can be placed in a few categories: (1) direct observations of products and growth, (2) development of models from FIA data, or (3) validation of an external model outputs. Of these, most assessments use traditional metrics of forest growth, but there are also a few more novel applications to be considered.

Studies that used FIA data to directly quantify forest products and growth were focused on either explaining the mechanisms controlling the distribution and growth of products or using the information in a supply chain modeling exercise. Bechtold et al. (1991) used FIA data from two successive inventory periods (1961–1972 and 1972–1982) to track changes in basal area growth rates in Georgia pine plantations to evaluate causes of reduced growth over the two inventory periods. Following this work, Reams (1996) used FIA to identify 20 plot locations of loblolly pine (*Pinus taeda* L.), which were sampled to provide radial growth data from tree increment cores. The previous study suggested that loblolly pine stands had shown decreased growth rates through the 1970s and early 1980s; however, this study updated growth data through 1989 and showed that while there was a trend of decreased growth in the 1970s, radial growth rates had recovered in the 1980s, which is in line with growth and yield estimates from FIA data for that period. Reams (1996) also noted that radial growth in loblolly pine follows a cyclical trend, with periods of reduced growth rates followed by periods of increased growth. Using a similar approach, Elias et al. (2009) used periodic mean annual volume increment growth data from repeat measurements of 30 accurately located FIA plots and local soil and acid deposition data to determine the effect of acid deposition on forest growth. Results showed that growth data from forest inventories could be used as potential predictors of acid deposition. Berguson et al. (1994) used FIA data from the Lake States region to develop stocking indices based on relations between tree height and canopy density. Long and Shaw (2005) developed density management diagrams from FIA plot data for even-aged stands of ponderosa pine (*Pinus ponderosa* Douglas ex P. Lawson & C. Lawson) for western United States land managers, and in a follow-up study, Long and Shaw (2012) developed density management diagrams for managers of even-aged stands of mixed coniferous forests in the Sierra Nevada range.

Other efforts have tried to link forest products and growth information with management decision making. Moser et al. (2009) linked landowner objectives to forest volume and diversity on small private woodlands owned by Midwest farmers. This study provided a more localized assessment of forest products that has applicability for small private landowners and could demonstrate the value of FIA data to groups such as family forest owners, state forest owners' associations, and the American Tree Farm System. Butler et al. (2014) used FIA data to provide variables used to model and map forest ownership categories; variables used included stand-level attributes and road density. Siry and Bailey (2003) used FIA data to track increased growth rates in pine plantations across 13 southern states, linking this to increased merchantable volume, harvest removals, and implications for lumber supply. Prestemon and Wear (2000) took a similar approach and used FIA data to track growth in southern pine stands in North Carolina. Harvest decisions and lumber supply were then modeled based on current timber values, operating costs, and the opportunity cost of nontimber forest products. Smidt et al. (2012) used FIA data and FVS-modeled growth to estimate the volumes of logging residue and non-merchantable biomass resulting from hypothetical harvests of forests in the southeastern United States. These volumes were used to explore the feasibility of using harvest residues for bioenergy production and the loadings of residues required to break even on production costs. Canham et al. (2006) and Papaik and Canham (2006) each conducted studies of forest competition in northern and southern New England forests, respectively. Each used data from FIA plots located across New England to parameterize models to explore the effects of competition on growth and yield. Following this, Canham et al. (2013) focused on forest disturbances in the northeastern United States and developed a model to predict stand harvesting based on total tree biomass and the proportion of basal area that could theoretically be removed from the stand. This approach is well suited to northeastern United States silvicultural practices; different parameters would be needed for the western United States where clearcuts, shelterwoods, and thinning treatments are more frequently applied.

Other approaches to using FIA for forest products and growth assessments have directly used FIA data to develop models of both individual-tree and stand-level attributes. Prestemon (1998) developed a model to predict merchantable tree and stand attributes from FIA data. Model outputs were validated with FIA data; models for softwoods and large-diameter hardwoods were found to be the most accurate for predicting log grade. Cao et al. (2002) presented a methodology for modeling individual-tree growth using FIA-based models specified for loblolly pine – shortleaf pine forests in Louisiana. Individual models for tree height, diameter, crown percent, and survival were developed based on FIA data from two subsequent inventory periods and integrated to produce a combined individual-tree model. Zobel et al. (2011) used FIA data from 1977, 1990, and 2003 to fit a series of empirical models for basal area growth in aspen forest types of Minnesota and determined that each period produced estimates nearly identical to those from simple empirical models, but that with increasing model complexity, the variance in the estimates from each dataset increased. Although the lack of older aspen stands prevented the fit of the best overall model, the authors believed that their model development approach could prove useful in other forest systems.

The final major use of FIA data for assessing forest products and growth has been the validation of outputs from modeling platforms external to the FIA program. Siry et al. (2001) compared FIA growth projections with productivity models for high-intensity management pine plantations in the southern United States. For these intensively managed areas, FIA data were found to underestimate growth by up to 94%. Siry et al. (2001) theorized that higher than expected growth and yield in southern pine plantations could be beneficial economically, as the southern pine market had been predicted to experience supply shortages. Pan et al. (2004) modeled foliar nitrogen concentrations and net primary productivity in mid-Atlantic forests and used FIA biomass data to validate wood production rate projections. Results showed that observation of foliar nitrogen concentration significantly increased predictions of wood production rates. Russell et al. (2013) used FIA data to spatially calibrate outputs from the Forest Vegetation Simulator – Northeast variant for 20 common species. After calibration, the submodel was found to underestimate 5-year basal area growth for all forest types across the northeastern United States, suggesting that it may be necessary to refit or reengineer the variant to more accurately represent the region's growth dynamics. Waring et al. (2006) developed a model to estimate site index and forest growth potential across the northwestern United States from MODIS remote sensing observations and climatic variables, validating model outputs using FIA data from 5263 plots distributed longitudinally along a steep climate gradient in Oregon.

In an application assessing a nontraditional forest product, Farrell (2013) used FIA data on the abundance, stand composition, and proximity to roads of both sugar maple (*Acer saccharum* Marsh.) and red maple (*Acer rubrum* L.) trees in 20 northeastern states. The goal of this study was to estimate the production potential of maple syrup in each of these regions, where several states with historically high syrup production were evaluated for how each state either fully utilized or underutilized its potential for syrup production. This study helps to demonstrate the value of FIA data for nontimber forest products and reminds the reader of the breadth of resources that forests can provide.

While the FIA program provides robust data for assessing forest products and their growth, data usage has faced challenges as the range of applications continues to grow. To increase the utility of FIA reports for timber applications, Teeter and Zhou (1999) developed a method for breaking FIA summaries into more detailed product groups such as sawtimber and pulpwood. With a targeted return interval of 5–10 years for each plot in the FIA system but a program desire to provide annual summaries, Lessard et al. (2001) developed a nonlinear, individual-tree, distance-independent annual diameter growth model to improve annual summaries by accounting for tree growth of plots that are not re-measured in a given year. Advances in wood utilization within the forest products market have changed the assessment of merchantable biomass (Domke et al. 2012*b*). Merchantable volume estimates have traditionally been measured to a minimum small-end diameter and any portion of the bole below this diameter has been left on site and not utilized in any way. Domke et al. (2013*b*) describe a method to estimate the volume within this previously missing portion of the dataset from already available FIA data.

With an increasing focus on ecosystem management and the spatial patterns that drive ecosystem functions, Woodall and Graham (2004) proposed a method for conducting point pattern analysis using clustered FIA subplots. While each individual subplot (0.01 ha) is too small for this analysis to be effective, the combined area of all four subplots (0.04 ha) on any given FIA plot can be re-arranged. Woodall and Graham (2004) observed that the arrangement of subplots does not have a significant impact on the results. Application of point patterns derived from FIA data could significantly improve our understanding of local competition and its effect on forest growth.

Climate applications

FIA data can be highly effective for monitoring and analyzing climate-related forest issues because of the tremendous spatial and temporal breadth of the program. The FIA program encompasses a vast spatial area larger than any other similar database (Gelfand et al. 2013). The database is free from any geographic bias, providing a proportionally representative sample in all forested areas (DeRose et al. 2013). The long-term nature of the data's collection with a near century-long field campaign provides the continuity necessary to detect long-term changes. Finally, the standardized methods used to summarize data at the county level present a tractable resolution for large-scale climate applications. Generally, these studies attempt to either detect changing climate conditions or predict future climate conditions, based on currently available FIA data, but in all of these studies, the use of FIA data can be broken into a few categories: (1) direct observations of change, (2) development and training of a model, and (3) validation of model outputs.

Several recent studies have used FIA data to link shifts in species distributions to changing climate. One of the first studies to identify shifts in species distributions was Woodall et al. (2009), which related species regeneration density to species biomass density and found that regeneration was preferentially occurring at more northern latitudes. Woodall et al. (2009) estimated that some species were migrating north at a rate of 100 km per century. Brady et al. (2010) took a predictive approach in which FIA data were used to develop a model for detecting changes in climate at large spatial scales. Desprez et al. (2014) and Hanberry and Hansen (2015) took a different approach, tracking geographic shifts in species distributions using FIA data. Desprez et al. (2014) tracked the distribution of blackgum (*Nyssa sylvatica* Marshall) in the eastern United States from two separate inventories in the 1980s and 2000 and showed how its abundance changed in different sections of its biological range. Hanberry and Hansen (2015) took a much larger and comprehensive approach, tracking changes in species distribution of 74 different species found across the United States over roughly the same 28-year period as Desprez et al. (2014). This study detected distribution shifts in 26 of the 74 species but found that this shift was not uniform. Roughly half of the species in Hanberry and Hansen (2015) showed shifts toward the north, while the other half showed distribution shifts toward the south; additionally, limber pine (*Pinus flexilis* (E. James) Rydb.) showed an expanding distribution in both directions. A key limitation in the use of FIA data is that the data do not extend past the United States (Hanberry and Hansen 2015), which means that some critical points of the spatial distribution may be missed. To get at some of the species-specific stand dynamics that climate might drive, Zhu et al. (2014) modeled the climate space of juvenile and adult trees using FIA data and found that for 77% and 83% of species, respectively, regeneration was occurring in warmer and moister areas than occupied by the adults.

Other studies have utilized FIA data for climate change modeling applications (Coops et al. 2009; Gelfand et al. 2013; Iverson and Prasad 1998; Iverson et al. 1999; Jiang et al. 2015; Pan et al. 2009). Gelfand et al. (2013) utilized FIA data to increase the projection scale of an integral projection model (IPM) for use in climate change. IPM modeling is typically a small-scale projection, often done at a plot level, which makes it unsuitable for large-scale climate applications. Linking plot-level projections from IPMs to FIA data allows the model to be scaled up to encompass large areas; in this study, the entire eastern United States is projected from IPMs. FIA is invaluable for this type of model scaling as it is a ground-based dataset that encompasses large enough areas to be suitable for climate analysis. Jiang et al. (2015) used FIA data for model development by linking current FIA-derived site index to soil and climate data. Modeled site indices were mapped under assumed conditions to produce forest productivity maps under varying scenarios. Pan et al. (2009) modeled changes in carbon sequestration due to changes in atmosphere, climate, and land use, while using FIA data to validate the output of their model. Iverson and Prasad (1998) and Iverson et al. (1999) used regression tree analysis of FIA data along with soil, climate, elevation, and land use data to predict changes in species distributions under a given future climate condition associated with a twofold increase in atmospheric CO_2 level.

The last set of studies used FIA data to validate outputs of models for current conditions. Coops et al. (2009) modeled species presence or absence for 3737 FIA plots across the west coast of the United States based on mean monthly climate conditions. The output was then compared back with the observed species on each FIA plot for model validation, resulting in 87% accuracy, but Coops et al. (2009) hypothesized that a broader set of climate factors would produce more accurate results. DeRose et al. (2013) exploited the incredibly high temporal resolution of FIA tree ring data by using dendrochronology for climate reconstruction to spatially track the El-Niño Southern Oscillation (ENSO) dipole, showing large shifts in the latitudinal range of the ENSO during recent centuries. This study also compared FIA tree ring data with equivalent data available from the International Tree-Ring Data Bank (ITRDB) and found that tree ring data from FIA had less variation than data from ITRDB. A possible explanation offered in this paper is that the ITRDB chronologies tended to be from highly drought-sensitive trees, while the FIA chronologies are taken from a systematic sample of the entire population of trees. In one of the largest forest inventory synthesis efforts, Hember et al. (2017) combined FIA data with other large-scale North American inventories to model the effect of drought on tree mortality for 65 species. Results showed that average mortality rates have increased over the last 50 years, but that mortality has also become increasingly episodic due to higher severity droughts.

While most of these studies have contributed new ways of understanding climate effects on tree species, a couple have brought out interesting discussions of FIA programmatic changes and limitations. Lintz et al. (2013) demonstrated that the change in sampling protocol in 2000, from a regional to a unified national approach, did not appreciably impact sampling errors when modeling the effect of climate on species distributions. Gibson et al. (2014) compared publicly available coordinates with true (untruncated) FIA coordinates for species distribution modeling in response to climate change for several juniper and piñon pine species and showed similar results. This, however, is one example of an application on a set of species that occupy a widespread dry and warm climate space. Although these results are promising, it is quite possible that the effect of plot location "fuzzing" could be quite dramatic on species that require more localized mesic growing environments. As modeling efforts proceed to increasingly finer resolutions, the demand for unperturbed plot coordinates will likely continue to increase as this will become one of the greatest bottlenecks to these efforts.

Forest health applications

Land managers are faced with the prospect of a changing climate and must deal with the implications that this has on forest health and disturbance patterns. The periodicity of FIA inventories, their large spatial scale, and the accessibility of the data make it a powerful resource for monitoring forest health. Similarly, their spatiotemporal balance and standardized collection protocols facilitate assessment of forest disturbance and recovery. Using FIA to predict forest health vulnerability and merchantable species availability following future composition shifts due to climate is a valuable application of FIA data (Smith et al. 2014). The use of FIA data in analyzing forest health and disturbances is among the most diverse covered in this synthesis, as it includes areas of general forest health, fire hazard, insects and pathogens, invasive species, and habitat suitability.

General forest health

In terms of monitoring general forest health, studies can be divided by the scale at which they analyze their FIA response metrics. Many studies operated at broad spatial or temporal scales, looking at trends in successional stages and forest structures, while others operated at finer plot- and tree-level scales to try to explain the mechanisms behind changes in forest health. Miles (2002) looked at the potential to use FIA data to monitor biological indicators of trends in forest health. From a group of 67 internationally recognized indicators, 11 were determined to be directly obtainable from FIA data alone, including assessing trends in forest type, area, and successional stages and diversity of forest species. Liu et al. (2003) and Zhang et al. (2004) both used FIA data to classify FIA plots into six ecological habitat types. These closely related studies applied different techniques, with Liu et al. (2003) using a *k*-nearest neighbor method to classify plots, while Zhang et al. (2004) used a Gaussian mixture model, but both showed accuracies in the 90th percentile. He et al. (2011) used Landsat TM/ETM+ imagery at a 500 m resolution to detect areas of disturbance in forests and used FIA data to identify the time of disturbance and subsequent regeneration. Schaberg and Abt (2004) assessed the impacts of hydrological data on the likelihood and impacts of harvesting by linking FIA data with specific watersheds from the USGS 6-digit hydrologic unit code (HUC6) database. Estimates of forest growth, mortality, and harvesting were projected forward to 2025, and the overall hydrological impacts on each watershed were estimated from these projections. In a more temporally focused effort, Sohl and Sayler (2008) used FIA data to provide stand age data for modeling changes in forest cover in the southeastern United States, linking historical changes in forests to local effects of climate. Dyer (2001) used witness trees from survey data from the 1787 Ohio Company Purchase to approximate presettlement forest conditions. These assumed conditions were then compared with current forest conditions taken from FIA data for the study area and the differences were used to infer forest changes. A similar approach was applied by Wang et al. (2009) to evaluate forest changes in New York State. Frelich (1995) used FIA data and old land survey data to track changes in old-growth forests around the Lake States from presettlement conditions. Hanberry et al. (2012) used a combination of historical survey data and current FIA plots to track trends of species homogenization and forest habitat mesophication in Minnesota. This study showed a general trend towards a later successional stage forest type, likely due to reductions of frequent disturbance in the subject forests.

At finer scales, studies have attempted to use FIA data to explain stand dynamics related to forest health such as regeneration, competition, and mortality. In a cross-scale analysis, Puhlick et al. (2012) used FIA plots and field soil samples to determine which site and stand factors had the most significant impact on regeneration of ponderosa pine (*Pinus ponderosa*) stands in the southwestern United States. FIA data were used at a more regional scale, while soil samples were used at a more local scale. Wang et al. (2013) used FIA data to drive the LANDIS PRO model, which predicts competition factors and disturbances from small processes at a tree level and scales up projections to a landscape level. Westfall and Morin (2013) used FIA data to model crown cover of individual trees based on tree-level attributes and established crown width models. Morin et al. (2015) looked at trends in mortality related to various crown health codes recorded by FIA; 2616 plots from the 1999 inventory were resampled in the eastern United States to assess which recorded crown health conditions resulted in eventual mortality. Meng and Cieszewski (2006) used data from the 1989 and 1997 FIA inventories in Georgia to look at the effect of spatial clusters on tree mortality; the results have the potential to explain the spatial spread of different agents of mortality.

Fuels and fire hazard

Following a century of fire suppression and other management actions that have increased stand densities and fuel loadings, wildfires are the most highly publicized disturbances to forested ecosystems. When compared with physical modeling of target forest structures, the geospatially uniform distribution of FIA data can be used to assess fuel and fire hazard spatially. Arriagada et al. (2008) used FIA data to estimate the gross cost of fuel reduction treatments ($1000–$9000 per hectare) based on harvesting smaller diameter trees in the western United States. This study did not consider the commercial value of the volume being removed, which could offset some costs. Chojnacky et al. (2004) modeled DWM based on FIA Phase 2 plots in the eastern United States and validated it against FIA Phase 3 plots. Chojnacky et al. (2013) then estimated DWM across the entire United States and made the resulting map available as an online web tool. Keane et al. (2013) looked at the accuracy of fuel classification systems, using two established systems and one new classification developed in their study from over 13 000 FIA plots. Low accuracies were found when fuel loadings from the classification were compared against actual plot values, which was attributed to high variability in fuel component loading even within classification categories. As one pathway to improve such assessments, Hudak et al. (2012) and Hudak et al. (2016) demonstrate the utility of *k*-nearest neighbor imputation for estimating fuel loads, which relies on the association between surface fuels and the overstory to estimate surface fuel loads indirectly as ancillary variables, rather than directly as the response variable in the model. By imputing a single nearest neighbor ($k = 1$), the variance in the imputed fuel loads preserved the variance in observed fuel loads.

In terms of crown fire assessments, Cruz et al. (2003) modeled canopy fuels and structure based on FIA plot-level attributes such as stand height and basal area. Estimates of canopy fuel loading were then produced for areas highly susceptible to crown fire in the western United States. Skowronski et al. (2007) used a combination of LiDAR and FIA data to model canopy structure and ladder fuels for New Jersey pinelands. The study found relatively high accuracy at larger scales but noted increased variability at plot scales. Woodall et al. (2005) linked fuel loads with atmospheric data to estimate fire risk level under variable fuel moisture levels. The end product was a large-scale fire risk map based on fuel loading and moisture levels. Through coupling United States census and FIA data, Zhai et al. (2003) linked fire probability, road proximity, wildland urban interface (WUI) proximity, education level of local residents, stand composition, management history, and fire history. A similar study by Munn et al. (2002) focused on harvest trends with increased proximity to urban areas by combining harvest data from FIA with census data in the southern United States. In general, the closer a stand is to urbanized areas, the less likely it is to be harvested, potentially due to impacts of public perception and opinion.

Insects and pathogens

Numerous studies have also taken advantage of FIA's damage codes to study the impacts and spread of forest insects and pathogens. One of the impetuses of this was when Cowling and Randolph (2013) called for increased collaboration between FIA and forest pathologists, specifically those working on fusiform rust, which primarily affects southern pine plantation species. Baker et al. (2012) used FIA and Minnesota DNR data from over 200 stands to evaluate the frequency of dwarf mistletoe in black spruce (*Picea mariana* (Mill.) Britton, Sterns & Poggenb.) stands. They found that FIA and Minnesota DNR databases underestimate the abundance of dwarf mistletoe by a large margin — roughly a factor of five. Similarly, Lamsal et al. (2011) used FIA data and a local northern California plot network to map the distribution of oak species susceptible to sudden oak death, the current status of infection, and the potential for future spread of the disease. Several studies have used FIA data to evaluate oak decline (Kromroy et al. 2008; Fei et al. 2011; Hanberry 2013; Knoot et al. 2015), which is a serious forest health issue that is attributed to a variety of causes including changes in climate, fire regimes, invasive species, insects and disease, and forest management practices. Randolph et al. (2013) investigated the potential to use FIA to track the presence of thousand cankers disease in black walnut (*Juglans nigra* L.) from tree attributes such as overall health and crown condition. Though the study saw limited temporal change in the abundance and presence of thousand cankers disease, the authors noted that this could have been due to an actual absence of the disease or an inability of the FIA program to detect the disease's presence. The authors discuss that accurately assessing the causality of tree mortality in the FIA database can be difficult with return intervals of 7–10 years. In a similar study, Shearman et al. (2015) used FIA to track changes in redbay (*Persea borbonia* (L.) Spreng.) resulting from laurel wilt disease and demonstrated potential in tracking mortality at plot, county, and state levels. Finally, Witt (2010) used FIA data to examine tree- and stand-level attributes associated with heart rot in aspen species. The results showed that older trees and larger trees were more susceptible to heart rot, but the author points out that this may be due to a longer exposure time to potential pathogens. The author also noted that FIA lacks any sort of genetic data that could be useful in detecting susceptibility to various forest pathogens.

Many other studies have focused on insect disturbance agents, including Thompson (2009), who coupled aerial detection surveys with FIA annual inventories in Colorado to track insect-caused mortality in lodgepole pine (*Pinus contorta* Douglas ex Loudon), finding a 10-fold increase over a 10-year period. Haavik et al. (2012) used FIA to identify red oak stands in Arkansas and then surveyed those stands to look for red oak borer presence. Not surprisingly, stands with increasing numbers of red oak borer showed increased red oak mortality. Moser et al. (2003) used FIA in a model run to provide recommendations to land managers on which pine species to favor in southern plantation forestry based on a combination of growth rates and predicted volume loss from various insects and diseases.

Invasive species

There has been a rise in the number, range, and severity of invasive species outbreaks impacting forests in the United States over the last several decades. The temporal continuity and spatial distribution of FIA plots allows analysts to identify and monitor the spread of these organisms to better understand mechanisms promoting their spread. Huebner et al. (2009) used FIA data to quantify the abundance of exotic and invasive plants in the Allegheny National Forest, Pennsylvania. The abundance of invasive species was linked to stand characteristics and to further identify potentially vulnerable areas prior to establishment of invasives. Similarly, Lemke et al. (2011) used FIA data to model the potential for invasion of Japanese honeysuckle in the Cumberland Plateau and Mountain region located in the southeastern United States. Japanese honeysuckle is a highly prolific invasive plant; using FIA to identify areas prone to invasion allows land managers to prepare for and possibly prevent the spread of invasive species. Hussain et al. (2008) used FIA data to identify common stand characteristics for areas with invasive plants, similar to the work done by Huebner et al. (2009). Hussain et al. (2008) also included economic and social factors such as land ownership and proximity to large cities as factors contributing to vulnerability to invasive species. DeSantis et al. (2013), in a study focusing on the emerald ash borer, linked FIA and climate data to map how the spatial distribution of ash species (*Fraxinus* spp.) overlapped with the optimal temperature range of emerald ash borer. They showed that ash species growing in the most northern latitudes of the range have potential to survive despite the tenacity and prolific nature of emerald ash borer, but the study was limited by lack of data outside the United States. Riitters et al. (2018) used over 20 000 FIA plots to quantify landscape pattern effects on the probability of invasive plant invasion and found that while proximity to road impacted invasion probability, proximity to agricultural land and forest fragmentation had the greatest impact. One of the more sophisticated approaches utilized a spatial association of scalable hexagons analysis in combination of FIA field plots, Forest Health Protection aerial surveys, and the MODIS active fire product to run Getis–Ord hotspot analysis to identify clustering of invasive plant occurrences, bark beetle activity, and fire ignitions (Potter et al. 2016). Such an analysis has widespread applications for identifying the origin and vector of invasive species.

Habitat suitability

Several studies have applied FIA data directly to wildlife-related research questions. Two of these studies explored the relationship between tree and stand attributes and the abundance of cavity trees, which are often favored as nesting sites by birds (Fan et al. 2003; Temesgen et al. 2008). Fan et al. (2003) used FIA to identify plots that had at least one cavity tree present and then evaluated common stand characteristics, with stand age and basal area identified as the most predictive attributes. Temesgen et al. (2008) also used FIA to identify common stand characteristics for sites with cavity trees but found stronger relationships with stand composition, density, site index, and quadratic mean diameter. Brooks (2003) used FIA data to track trends in early successional stage forests in the northeastern United States. Despite their temporary nature, these forests provide critical habitat for wildlife species across the country. A similar study used FIA to examine relationships between birds and forest habitats at large spatial scales (Fearer et al. 2007), where FIA data were used to produce a bird-habitat database by combining FIA's forest habitat data with information from the USGS Breeding Bird Survey database to model bird–habitat relations across ecoregions. Similarly, Twedt et al. (2010) combined FIA and Breeding Bird Survey data to predict how decadal changes in forest conditions will impact avian species abundance and identified species that will be winners and other species that will be losers. Zielinski et al. (2006) and Zielinski et al. (2012) in two consecutive studies used forest attributes in FIA data from northern California to model resting habitat for fishers. Finally, Welsh et al. (2006) described a methodology to model wildlife habitat from FIA variables that could be applied to any species. Such models could be developed from co-occurring forest inventory and wildlife species use observations, potentially highlighting an area for future joint data collection efforts.

While FIA data have informed findings across an amazing range of applications in assessing forest health, use of the data has not been without its challenges. A consistent and repeated criticism of the dataset is confusion surrounding the FIA damage codes, with many studies remarking that it is necessary to have an FIA expert involved to decipher the data structure and coding protocols. Prior to the consolidation of FIA programs that resulted in the annualized FIA inventory, problems with data continuity and consistency made the temporal tracking of mortality agents nearly impossible from the dataset. Following the program change, Shaw et al. (2005) used FIA annual inventory plots to track mortality in Pinyon–Juniper forests and were able to discern interannual variations in drought-induced mortality. Westfall and Woodall (2007) examined the reliability of fuel estimated from FIA data and observed that many of the measurements were not repeatable and that roughly one-third of all measurements had biases that made the data unreliable. The paper further discussed the causes of measurement error and suggested that small tweaks in FIA protocols such as emphasizing key measurements in training and eliminating recording errors through electronic systems could increase measurement consistency and overall data reliability. Another study noted that certain forest pathogens such as *Armillaria* fungi, which are associated with root decay in many western plant species, are difficult to detect when signs are found on the tree roots and require destructive sampling. In response, Hoffman et al. (2014) surveyed established FIA plots in Arizona for the presence of *Armillaria* fungi, utilizing a new supplemental subplot 36.6 m away at 300° azimuth from the center of the existing FIA subplot. The destructive nature of the sampling necessitates that a new subplot be established outside the current FIA plot. The method presented can be used successfully to sample for *Armillaria* without disturbing the rest of the FIA plot and can be readily incorporated into the current FIA sampling protocol. While the method is feasible, its implementation would require increased time and cost in sampling and data archiving.

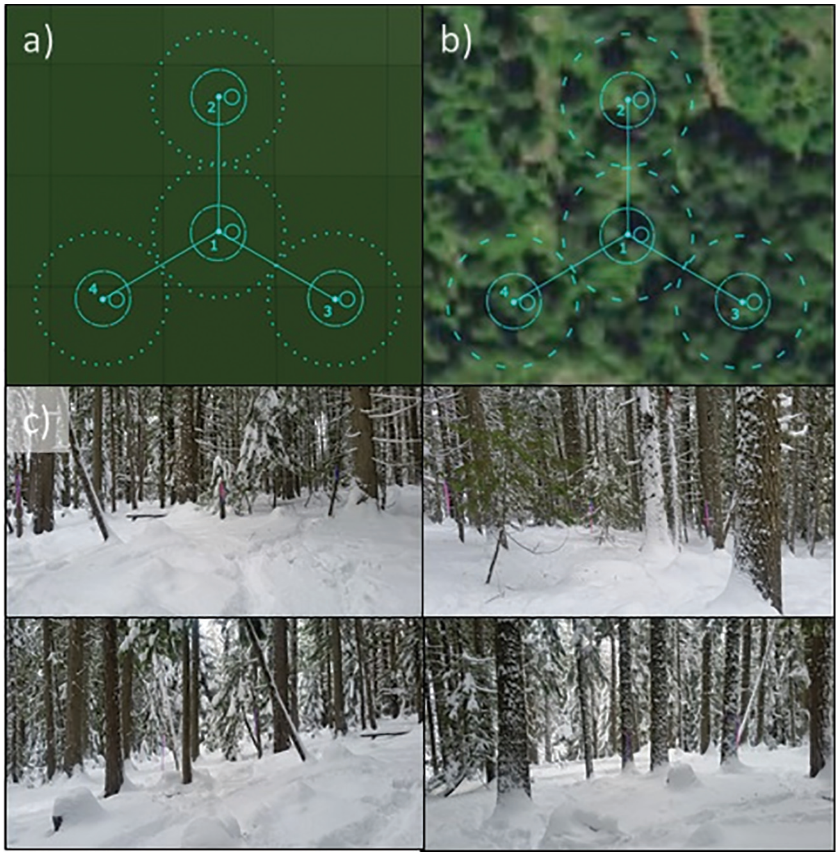
Remote sensing applications

The association of FIA with remote sensing datasets has been a two-way street, with early mergers of the datasets focusing on improving regional- and national-level reporting of FIA (McRoberts et al. 2002*a*). FIA started using remotely sensed imagery in the 1960s via aerial photography to increase the precision of inventory estimates by improving the identification of forest type and their extents (Hansen 1990). Although satellite sensor data were later employed to improve forest area estimates (Hansen and Wendt 2000), the limited temporal availability of these data led to studies not meeting FIA precision standards (McRoberts et al. 2002*a*). Most modern studies attempting to develop models from field observations with remote sensing data utilize some form of multivariate regression or classification scheme. Brosofske et al. (2014) provided a summary of the advantages and limitations of various modeling and mapping methods, e.g., regression, decision tree, and imputation, for use with remotely sensed datasets. Plot data imputation techniques have been demonstrated with LiDAR and Landsat remote sensing datasets to produce forest type assessments with improved spatial precision (Ohmann and Gregory 2002; Ohmann et al. 2011; Hudak et al. 2008, 2012; McRoberts et al. 2002*b*, 2007; Powell et al. 2010). Although the earlier sections of this synthesis already highlight many studies that have utilized FIA data in combination with well-established remotely sensed image datasets, these studies were not self-identified as being remote sensing studies. Within all of the reviewed applications of FIA for remote sensing, FIA data have been used for both model development and validation by the different authors. Most of the studies identified as serving remote sensing purposes attempt either to create broad-scale forest biomass estimates or to classify and map forest types and their characteristics.

One of the earlier uses of FIA with remote sensing for biomass mapping was when Blackard et al. (2008) used FIA estimates of total biomass to develop unique total biomass regression tree models for 65 ecological zones across the conterminous United States, Alaska, and Puerto Rico. The model-predicted biomass estimates came from MODIS, National Land Cover Dataset, and climate observations and were validated through a randomized block withhold of FIA plots from each ecological zone. Model predictions narrowed the range of local biomass values but seemed to accurately represent regional and national estimates from both FIA summaries and other mapping efforts. At an even broader scale, Pflugmacher et al. (2008) developed a biomass model based on tree heights from FIA plot data and applied the model to forest heights derived from the Geoscience Laser Altimeter System (GLAS) to estimate global forest biomass. Results from this biomass estimation were validated against a separate set of FIA plots. GLAS is the first spaceborne LiDAR system, and the sensor is carried onboard NASA's Ice, Cloud and Land Elevation Satellite (ICESat). The use of GLAS for biomass estimation allows for estimation of biomass at a scale not previously possible. However, if the area of interest is particularly large, e.g., the entire east coast of the United States or an entire nation, then the coarser resolution MODIS dataset may be more practical as it will provide a sufficient pixel density each day, as compared with Landsat every 16 days. In a smaller scale application, Kwon and Larsen (2012) used FIA plots located across eastern United States forests to validate gross primary production (GPP) estimated from MODIS data. A set of screening variables was applied to the FIA plots used in validation, which improved the correlation between MODIS GPP and FIA NPP from 0.01 to 0.48. Following this, Kwon and Larsen (2013) identified an optimal mapping resolution for MODIS-based biomass estimation at 390 km^2, this time using NPP from MODIS. Finally, looking at temporal biomass changes, Powell et al. (2010) developed models of biomass fluxes from FIA data and annual Landsat images over a 20-year period. Once the annual Landsat response parameters were smoothed, the projected maps were able to depict the location and timing of forest disturbances and their subsequent regrowth, providing a finer temporal and spatial representation of biomass flux. Landsat products, at a 30 m pixel resolution, will provide a more detailed estimation than a 500 m resolution MODIS pixel. Each of these models employs different model development and validation techniques, which makes their direct comparison difficult. After noticing these inconsistencies in the broader remote sensing literature, Riemann et al. (2010) proposed a method for evaluating the effectiveness of a remotely sensed dataset using FIA as a reference to validate remote sensing data. Utilizing such a consistent framework for validation provides essential information on the type, magnitude, frequency, and location of errors in a dataset, allowing for direct comparison between multiple model development techniques.

Forest type classification and estimation of forest structure and composition parameters are also common applications of remote sensing data that are integrated or validated using FIA data. Haapanen et al. (2004) used the *k*-NN imputation method with FIA and Landsat TM/ETM+ data to map land cover types in the Great Lakes area with accuracies around 90%. Land cover was classified as forest, nonforest, and water at the 30 m resolution of Landsat TM/ETM+. White et al. (2005) used FIA and Southwest Regional GAP plots to validate estimates of tree canopy cover from the vegetation continuous field (VCF) tree cover product derived from MODIS. Results compared with FIA and Southwest Regional GAP plots were similarly biased, while the MODIS VCF consistently underestimated canopy cover and the negative bias increased as canopy cover increased. Sivanpillai et al. (2007) evaluated the use of Advanced Very High-Resolution Radiometer (AVHRR) imagery to replace aerial photo methods used in Phase 1 FIA estimates of forest cover. AVHRR produced lower accuracies than the aerial photography at a plot level, misidentifying fields with sparse trees as forest and recently harvested pine stands as nonforest. However, at the county level, estimation accuracies were within 95%. Chojnacky et al. (2012) developed a Phase 1 mask with MODIS to increase vegetation cover types from 2 to 5 to improve forest attribute data from FIA in these sparse pinyon–juniper woodlands, which had been a noted limitation from previous FIA-

Fig. 4. Example FIA plot, overlaid on imagery from (*a*) Landsat OLI, 30 m pixels, and (*b*) NAIP, 1 m pixels, and (*c*) sample photos of subplot 1 taken from plot center and arranged clockwise: north, east, south, west. [Colour version online.]



related research efforts in the region. Leefers and Subedi (2012) used FIA data to validate forest type estimates in Michigan derived from other state and national forest inventory programs and a state remote sensing dataset. Although field-based inventories showed a higher level of agreement with FIA observations of forest type, the authors suggest that their inability to access unperturbed FIA plot locations may have significantly increased the predicted errors of the remote sensing dataset. Each of Sader et al. (2005), Thomas et al. (2011), and Schroeder et al. (2014) combined annual Landsat imagery with FIA data to improve estimation and detection of forest disturbance. Given that the FIA sampling protocol only has each plot re-measured every 5 to 10 years with a spatial resolution of roughly 2428 ha, use of annual Landsat imagery can provide additional data to detect disturbance events. With the launch of Landsat 8 in 2013, the proposed launch of Landsat 9 in December 2020, and the goals of the Data Continuity Mission, the potential applications integrating FIA and Landsat will only increase (Landsat 2016; Fig. 1). FIA plots also work well to approximate the size of 30 m Landsat image pixels that are roughly equal to the area of one macroplot, and each subplot is roughly one-fifth the area of a Landsat pixel (Fig. 4). On the other hand, the round macroplots and systematic subplot configuration do not align well with the square pixel grid, which inevitably adds noise to relationships, especially wherever different condition classes prevail due to forest edges in the scene (Ohmann and Gregory 2002).

Although Landsat and other moderate- to high-resolution datasets have been shown to typically provide fairly accurate estimates of stand variables, within highly variable landscapes, accuracies can break down when trying to estimate tree species, understory species, successional stage, and age class (Liu et al. 2008). One of the earliest uses of FIA with remote sensing to estimate tree and stand parameters was when Gill et al. (2000) used FIA data to validate tree size and crown closure estimates from Landsat-derived vegetation maps for northeastern California, demonstrating the strength and cost effectiveness of using FIA data for validation purposes. Zhang et al. (2009) used Landsat TM data and FIA data to map species composition and tree age in the Missouri Ozark Highlands. Landsat imagery was used to define ecotypes, which were then stratified by composition and age from FIA data. Taking this further, Al-Hamdan et al. (2014) used Landsat TM data to develop a model to predict the size class and wood type of stands in the southeastern United States. Size class was categorized as either sawtimber or saplings, and wood type was categorized as either hardwood or softwood. FIA data for the study region was used to validate the model predictions, which showed high predictive power. Wang et al. (2006) created a three-dimensional map of the forest landscape in the Washburn District of Wisconsin by integrating FIA, Landsat, and the Forest Vegetation Simulator (FVS). Forest types were classified using Landsat imagery, and data from FIA plots within each forest type were used in a 50-year FVS simulation. The most recent integration of Landsat imagery with FIA data came from Wilson et al. (2018), who demonstrated that the Landsat time series can be utilized through harmonic regression to achieve a two- to three-fold increase in explained variance over using monthly image composites. The ability to fully utilize time series observations along with the report FIA field plots could greatly advance our ability to map forested landscapes. Popescu et al. (2002) highlighted the potential of airborne LiDAR data to be integrated into FIA by modeling tree heights and validated the measurements using ground plots established following the FIA protocol (not actual FIA program plots). Such integrations of LiDAR with FIA plot data have become much more frequent and have been leveraged to characterize highly heterogeneous landscapes such as Hawaii and Alaska.

While the combination of FIA and remotely sensed data are well established, there are some limitations that need to be addressed. Most applications of remotely sensed data require highly accurate ground control points, which become increasingly important at higher spatial resolutions. Even when researchers undertake the legal requirements to have access to untruncated FIA plot locations, most FIA plots are located using recreational-grade GPS systems, which typically have accuracies of less than 3–7 m (Anderson et al. 2009). While this accuracy level is not limiting with MODIS pixels, reliable use with 30 m Landsat pixels and spatially precise, point-based LiDAR datasets requires accurate plot location data.

Discussion of FIA program

The temporal continuity, spatial balance, and consistent protocols of the FIA program make the dataset particularly well suited for the incredible range of applications that have been described. Although much knowledge has been amassed through the synthesis and application of FIA data, advances in statistical techniques and remote sensing methodologies are pushing the dataset limits and there is increasing acknowledgement of these new limitations within the FIA program and its protocols. As the FIA program has grown in both scope and complexity since the United States 1998 Farm Bill, which incorporated many elements of forest health monitoring into the FIA inventory protocols, a growing list of limitations has been formed. While this list has continued to grow, many solutions have been put forward and some have already been adopted by the FIA program, potentially opening other exciting avenues of investigation.

Limitations

Perhaps the most widely recognized limitation of working with FIA data is the confusion that exists around data coding, interpretation, and definitions. As Kromroy et al. (2008) remarked, damage codes in FIA data are unique to the program and are difficult to interpret and understand to non-FIA users. Although studies such as Bechtold and Patterson (2005) provide detailed descriptions of the program and many resources can be found related to the program, there is still a lack of clear definitions. Currently, the simplest solution is to collaborate with an FIA researcher who understands the intricacies of the program. Because of this, there has been a growing call for improved user manuals designed for non-FIA researchers such as industry and academic scientists or even the general public, which could greatly improve user understanding. Such a manual could also make the data more appealing to a larger audience and increase the utilization of this vast and powerful resource. Revised user manuals and a simplified version of the program framework could also make it more feasible for other countries to adopt and implement similar monitoring protocols based on the FIA design, extending the scope and inference of future datasets available more broadly to researchers.

In a study by Roesch et al. (2012), it was revealed that FIA's current techniques for area estimation of forest land categories suffers from higher bias and mean squared error than two more recently developed techniques. While not presently addressed, adopting one of these new approaches has the potential to reduce error in all FIA reports beyond the plot level as errors in area estimation will propagate through. Such changes are particularly important for broad-scale applications such as carbon pool monitoring and greenhouse gas modeling.

Another complicated and growing limitation of FIA is access to untruncated sample locations. FIA has long been conscious of this concern and took time to demonstrate that the "fuzzing" process has minimal impact on remote sensing models developed with moderate-resolution imagery (Healey et al. 2011). However, this issue has only increased as modeling efforts and remote sensing capabilities have advanced to finer spatial resolutions. The "fuzzing" of publicly available plot locations is congressionally mandated by the need to protect data integrity from being used against private landowners for various reasons (McRoberts et al. 2005). However, empirical models associating plot-level FIA data with spatially precise remote sensing data require accurate plot locations. Furthermore, imputation of forest inventory parameters using technologies such as LiDAR requires that plot locations are recorded and documented to sub-meter precision, which greatly exceeds that of the recreational-grade GPS systems currently in use throughout much of the FIA program. In the near future, FIA will increasingly be called upon to streamline access to accurate, untruncated plot locations, while maintaining the legal obligation to protect data integrity. Creating a simplified pathway to grant researchers access to untruncated sample locations will facilitate more accurate modeling and mapping of forest parameters from increasingly resolute remote sensing products.

Recent improvements

FIA has already implemented improvements to address other acknowledged limitations. FIA's prior focus on purely merchantable biomass allometric relationships received criticisms, largely as a result of technological advances in utilization of non-merchantable biomass. It has been noted that the older methods did not account for biomass in a tree bole past a small-end diameter or the contribution of other biomass pools such as tree branches and foliage. To resolve this issue and provide a more robust estimate of total biomass, Domke et al. (2012*a* and 2013*b*) demonstrated how estimating biomass with the component ratio method and refining total stem biomass estimates can improve accuracies when estimating both merchantable and total biomass. These new methods have since been adapted into the FIA program for biomass summarization.

An additional long-standing consequence of the FIA systematic sampling design is the limited representation of rare objects of interest such as very large diameter trees. In response to this issue within the Pacific Northwest Region of the FIA program, Roesch and Van Deusen (2010) demonstrated that inclusion of 17.95 m radius macroplots can capture rarer large trees with high accuracy and discussed how such a protocol could be adapted to monitor most other rare objects of interest in different regions. Other similar criticisms and resultant research have resulted in proposed changes in FIA sampling protocols to allow for additional monitoring of specialized observations. To allow for destructive measurements such as root samples for *Armillaria* monitoring, Hoffman et al. (2014) suggested installing a supplemental subplot located 36.6 m from the existing plot center. This subplot could be rotated circularly around the plot center for each measurement cycle to allow locations of destructive samples to recover and not impact the primary sample.

In recent years, there have also been concerted efforts to improve both the spatial and temporal representativeness of FIA data. Although the area encompassed by the FIA program is already vast, two efforts have sought to increase the area surveyed. The early history of forest inventory work within United States territories and Hawaii is relatively sparse and sporadic, with only Puerto Rico and Hawaii having ever received more than one inventory prior to 2000 and many territories never having been inventoried. Following the 1998 Education and Reform Act that charged FIA to standardize the sampling of all United States forest lands, including Alaska, Hawaii, and all territories, the FIA Tropical Island Forest Inventory Work Group put forward a proposal to adapt the common FIA protocols for working in tropical environments (Willits et al. 2000). Following the standard FIA protocols implemented in the continental United States, inventories of Hawaii and the island territories were planned and began in 2001. However, to ensure that these inventories were representative of the ecological complexity found in these tropical systems, after the initial hexagonal grid was installed for plot selection in forested areas, unique forest types found to be underrepresented had additional sample locations randomly selected until 10–15 samples were located in each forest type (Brandeis 2003). Due to logistical challenges of working in these regions, inventories of each of the United States territories is implemented on a focused 5-year schedule instead of on the annual cycle as within the coterminous United States. The use of a similar minimum number of representative samples for unique forest systems could address related user critiques to improve our understanding and modeling of these smaller populations. Within these tropical systems, emerging novel research into the spatial distribution and abundance of endemic endangered species is highlighting the importance of FIA in the tropics (Rojas-Sandoval and Meléndez-Ackerman 2013). Additionally, work is starting to investigate the effects of FIA plot phase intensity and density, along with the benefits of merging FIA and LiDAR data in quantifying the forests of Hawaii, finding that the more intensive plots have a greater benefit over standard Phase 2 plots in quantifying aboveground forest carbon and that LiDAR is a logical and affordable way to significantly improve these estimates in heterogeneous areas (Hughes et al. 2018).

In a further effort to expand the inferential utility of FIA data, Barrett and Gray (2011) argued for a more intensive FIA monitoring system in the boreal region of Alaska; this has high importance given that extreme northern regions are proving to be the first to show effects of altered climate conditions. Since this publication, the FIA program has begun establishing and inventorying plots in the Alaska interior boreal forest at the proposed density of one plot for every 12 000 ha, or one-fifth of the FIA plot density in the coterminous United States. Utilizing the first Alaska interior boreal forest FIA acquisition of 67 plots in 2014, Ene et al. (2018) demonstrated that merged FIA plots with aerial LiDAR sampling over such large landscapes can significantly enhance estimates of forest characteristics. While many of these changes have long been sought by users, there is still a large user base that would also ask the FIA to reduce or eliminate methodological changes as these will introduce issues for the long-term continuity of the dataset.

Future directions

FIA is a continuously evolving program in response to a growing list of user needs. FIA priorities are based on its Strategic Plan, which is currently framed by the United States 2014 Farm Bill. To meet program requirements and user needs, FIA has outlined the following focus areas: (*i*) bring data collection to "full field operations," which means annually measuring 10% of the plots in the west and 15% in the east and providing an annualized program in all of Alaska; (*ii*) enhance timber products monitoring; (*iii*) enhance forest landowner studies; (*iv*) improve carbon and biomass estimates; (*v*) expand land use and land cover monitoring to include all lands; and (*vi*) adapt and expand the inventory to urban forests. Funding increases are prioritized to bring data collection to the 20% annual measurement specified in the United States 1998 Farm Bill. Other identified focus areas include increasing outreach, engagement, communication, and dissemination efforts (Shaw 2017). These efforts will have a multipronged approach that will be split between online content, interactive content, and workshop and training opportunities. The hope is that through these efforts, user knowledge and understanding gaps such as that of database coding can be significantly narrowed and that accessibility to the FIA database will be substantially eased. To address some of these issues, the FIA program has created tools such as the Spatial Data Services team (https://www.fia.fs.fed.us/tools-data/spatial/) to assist the public with data acquisition, spatial summaries, spatial overlays with geospatial data, and gaining access to actual plot coordinates in some cases.

Following direction from the United States 2014 Farm Bill, the FIA program was expanded to create Urban FIA (UFIA) with its own sampling protocols. The UFIA protocols were piloted in 2014 in Austin, Texas, and Baltimore, Maryland (Vogt and Smith 2017). Importantly, UFIA's implementation has been intensified to one plot for every 354 ha, and existing FIA plot locations that fall within forested areas of defined city limits will in the future be inventoried using both FIA and UFIA protocols. Plans for the program are to expand as funding and partnerships allow, with 14 cities participating in UFIA in 2016, and further expanding to include all UFIA regions in 2017 (Vogt and Smith 2017). Recent work is investigating ways of merging these datasets for rural–urban landscape assessments (Westfall et al. 2018).

There are other ongoing efforts focused on expanding the temporal inference and, thereby, the temporal applications of the FIA database. DeRose et al. (2017) outlines the efforts behind developing a tree-ring dataset based on >14 000 tree cores from the Interior West region of the FIA program. Although this is an ongoing effort, more than 3000 tree cores have already been fully crossdated for the eight-state region. One of the initial goals of the data is to link it with the FIA plot database for use in development, calibration, and validation of forest growth and yield models such as the Forest Vegetation Simulator. In the last few years, the Pacific Northwest region of the FIA program has begun providing additional tree cores for processing within the database. As the database continues to grow, it will represent the highest resolution means of reconstructing climatological records across the western United States. Efforts such as these are only possible because of the individuals involved in the FIA program and will result in additional future research opportunities. In addition, the FIA program and other NFI datasets have considerable potential to be used as baseline and monitoring data when assessing vulnerabilities to critical ecosystem goods and services or in the development of spatially explicit disaster early warning systems (Smith et al. 2014).

Conclusion

The FIA program provides a comprehensive forest inventory annually to inform a wide and rich range of natural resource science and management applications. The public availability and use of the data for any purpose further increases their value. The intricacies of the FIA inventory design can be confusing for non-FIA users and the exact definitions can be difficult to interpret. The data are excellent for large-scale analysis and are more applicable over larger areas than smaller ones. The large spatial and temporal scales make FIA excellent for long-term analysis on multiple themes such as climate monitoring, trends in carbon stocks, and changing forest growth rates.

Most applications of FIA data have attempted to use it in a few ways. At its most basic application, FIA data summaries have been mined to understand coarse-scale forest distributions and ownerships either at the county scale or through course-resolution remote sensing products. The next level of application commonly utilizes FIA data in the development or validation of a modeling system. To date, the majority of FIA-related research has operated in this way. Finally, the more unique applications of FIA data are those that have tried to extend data utility by assessing characteristics and process mechanisms not found in the FIA database such as creating point process models or using FIA to impute and then model landscape respiration processes. For either of these last two application categories to continue to expand, certain challenges need to be overcome within the FIA program. For researchers to effectively embrace the FIA database and utilize it in the most cutting edge ways, they will need to be able to utilize the FIA database in conjunction with statistical processes and remote sensing datasets that are continually being designed for finer resolutions. This means two things: (*i*) the FIA will need to provide users with a simplified and more understandable key to FIA data collection and coding protocols and (*ii*) the FIA will need to find ways to more readily assist an expanding subset of users who need to accurately associate remote sensing data to plot-level FIA data at the untruncated plot locations.

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