

ARTICLE

Methods, Tools, and Technologies

Robustness of ecological indicators to species misidentification in the national forest inventory of the United States

Jonathan Knott¹  | Jianmin Wang²  | David Walker³  | Grant Domke¹  | Songlin Fei² 

¹USDA Forest Service, Northern Research Station, Forest Inventory and Analysis Program, Saint Paul, Minnesota, USA

²Department of Forestry and Natural Resources, Purdue University, West Lafayette, Indiana, USA

³USDA Forest Service, Southern Research Station, Blacksburg, Virginia, USA

Correspondence

Songlin Fei

Email: sfei@purdue.edu

Funding information

Northern Research Station

Handling Editor: Franco Biondi

Abstract

Longitudinal data are essential to assessing change in environmental parameters over space and through time. This is particularly true in forest ecosystems where demographic patterns are controlled by many biotic and abiotic factors that may only be observed through repeated measures of tree (e.g., height, diameter, status), stand (e.g., tree density, litter depth), and site conditions (e.g., evidence of disturbance). Data from the United States Department of Agriculture Forest Service, Forest Inventory and Analysis Program (FIA), support a variety of research and reporting efforts in forest resources and ecology. Remeasurements of the same plots provide invaluable information about the temporal dynamics of forest ecosystems. However, changes in attributes between remeasurements, such as species identification code (SPCD), can impact a variety of forest measurements such as species richness, species range dynamics, and carbon estimates. Here, we linked over 12 million tree remeasurements from approximately 140,000 FIA plots to explore how SPCD changes can lead to differences in key indicators of forest dynamics. Our workflow identified >114,000 trees with SPCD changes, with the frequency of SPCD changes highest in the southeastern United States. Two SPCD correction methods—adjusting a tree's SPCD based on either the earliest or the most recently recorded SPCD—led to species range centroids that differed by 0.3–24.5 km. Plot-level species richness varied by ± 4 species between the two SPCD correction methods, but many plots (58%) had the same richness despite reassignment of individual trees to different SPCDs. Tree-level carbon stock estimates were correlated between the two SPCD correction methods, but some trees were more sensitive to changes when species-specific allometric model form, coefficients, and/or carbon fractions changed. However, population estimates of parameters such as carbon stocks per unit area were robust to SPCD corrections because trees with consistent SPCDs vastly outnumbered trees with SPCD changes. Our results illustrate that decisions on how to

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2025 The Author(s). *Ecosphere* published by Wiley Periodicals LLC on behalf of The Ecological Society of America.

handle nuances in remeasurement data can have substantial implications on the biological and ecological conclusions drawn from large-scale, strategic-level inventories such as the national forest inventory in the United States.

KEYWORDS

carbon, FIA, Forest Inventory and Analysis, national-scale volume and biomass (NSVB), richness, species code, species distributions

INTRODUCTION

National forest inventories (NFIs) provide a wealth of information on the status and trends in forests globally. In the United States, the NFI is conducted by the US Department of Agriculture (USDA) Forest Service, Forest Inventory and Analysis Program (FIA). The FIA program is the largest, most comprehensive forest dataset for the United States and is among the most robust NFIs globally (Tomppo et al., 2010). FIA data support a variety of regional-, national-, and global-scale research and reporting activities (Tinkham et al., 2018), including the US greenhouse gas (GHG) inventory which is submitted to the United Nations Framework Convention on Climate Change (UNFCCC) on an annual basis (Domke et al., 2023; US EPA, 2024). The UNFCCC's "TACCC" principles (IPCC, 2019)—transparency, accuracy, completeness, consistency, and comparability—are core to the work FIA does in support of international GHG reporting. Moreover, remeasurements on the same plots can provide the understanding of temporal dynamics of the forests in response to climate change, management activities, and other factors at species, community, and ecosystem levels (Fei et al., 2017; Fei & Steiner, 2007; Knott et al., 2020).

While FIA field sampling protocols are designed to meet precision standards and include a robust system for quality assurance/quality control (QA/QC), FIA data are complex and not without error, as there is some amount of subjectivity by the field crews, such as identification of species, attribution of disturbance agents to dead trees, and quantification of tree damage such as rot, cull, and broken tops, among others (Bechtold & Patterson, 2005; USDA Forest Service, 2023). Data from FIA's QA/QC checks showed some inconsistencies between data collected by FIA field crews and follow-up QA/QC crews (Yanai et al., 2023). Another type of inconsistency is "nonresponse"—the inability of FIA plots to be sampled, most often due to hazardous conditions and denied access on private land—which occurs throughout the United States, with higher rates in the northern region (Westfall et al., 2022). In addition, remotely sensed data have shown potential mismatches between the data

collected by FIA and data collected from airborne and spaceborne platforms (Knott et al., 2023). However, the relatively small amount of missing or erroneous data is usually balanced by the large, robust sample; it takes a large quantity of data issues to break the assumptions of FIA's statistically representative sample (Domke et al., 2014).

Longitudinal data provide an opportunity to not only analyze the current status of forests but also track changes in forests over time. The FIA program continues to collect more data on existing plots, expanding the temporal record since the annualized inventory began in the late 1990s. Plots are remeasured every 5–10 years, and each state has completed at least one remeasurement of plots in the contiguous United States (CONUS) except Wyoming, with some plots being measured six times in the eastern United States. However, as the temporal record grows, new sources of error are coming to light.

One of the key variables in the FIA database is tree species identification code (SPCD). Species identification is foundational as allometric models for volume, biomass, and carbon used by the FIA program rely on SPCD (Westfall et al., 2023), and species range dynamics and species richness can be sensitive to misidentifications (Costa et al., 2015; Rodrigues et al., 2022). The process for changing SPCD requires the field crew to acknowledge in the data logger that the tree was misidentified in the previous measurement (USDA Forest Service, 2023). However, the FIA database retains the original SPCD for earlier records rather than correcting previous records or, vice versa, locking in the original SPCD as a variable that is unable to be changed by the field crew. Here, we aim to provide (1) a simple method for linking trees through time in the FIA database to determine when SPCD changed between remeasurements and (2) case studies highlighting the potential impacts of SPCD changes on species range centroids, species richness, and carbon stocks of US forests.

MATERIALS AND METHODS

The FIA program collects in situ data on over 140,000 forested plots across the CONUS, Alaska, Hawaii, and most of the US Territories and Affiliated Islands, using a

semi-systematic, probability-based sampling design (Bechtold & Patterson, 2005). Plots are remeasured approximately every 5–7 years in the eastern United States and 10 years in the western United States under the annualized sampling design. Plots in the western United States (except for plots in Wyoming) have completed an initial measurement and first remeasurement, while plots in the eastern United States have completed an initial measurement and at least two but up to five remeasurements as of 2024 (Renwick, 2023). FIA plots contain four 168 m² (0.04 acre) circular subplots arranged in a triangular formation with one central subplot (Bechtold & Patterson, 2005). A 13.5 m² (0.003 acre) microplot is nested within each subplot. Trees ≥ 12.7 cm (5 in.) dbh are measured on subplots, while trees 2.54–12.7 cm (1–5 in.) dbh or diameter at root collar (DRC), depending on height, are measured on microplots. Here, we used data from the CONUS on plots that have been remeasured at least one time (i.e., all CONUS states except Wyoming) and uploaded to the FIA database as of 6 January 2025 (<https://apps.fs.usda.gov/fia/datamart/datamart.html>).

Our method for linking trees through time and identifying species mismatches followed a relatively simple workflow. First, we compiled all live tree records (tree status code, STATUSCD = 1) from the annualized inventory, approximately 12.3 million records in total. We selected the most recent record of trees that were measured at least twice by selecting tree records that had the previous tree control number column populated (PREV_TRE_CN) but their tree control number (CN) not included in any other tree record's PREV_TRE_CN. Next, this subset of trees' PREV_TRE_CNs were used to select CNs of the remaining trees. This process was repeated, linking the trees to their previous measurements until there were no more matches. Trees that were not included in any remeasurements were assumed to be either in plots measured once or only alive for one measurement. Plot control numbers (PLT_CN) were used to select trees from the most recent inventory and to filter plots from base-level sampling intensity (approximately one plot per 2400 ha).

We evaluated whether there were changes in SPCD between remeasurements of individual trees and applied two methods for correcting SPCD changes (hereafter “correction scenarios”). First, we used the current SPCD and back-corrected previous measurements. This correction scenario reflects that remeasurements provide additional evidence of a tree's true SPCD as larger, older trees are usually easier to identify than younger trees, and the field crew had to acknowledge the SPCD change in the data logger. Second, we used the first recorded SPCD and carried it forward to the future remeasurements. This correction method follows a possible inventory protocol that initial species identification of a tree could be

“locked in” by the FIA program rather than allowing it to be changed over time.

We used multiple case studies to explore the potential effects of species misidentification. First, we assessed differences in species' range centroids under the two correction scenarios. We selected species that had at least 1000 trees with SPCD changes. We filtered the study dataset to only include plots from base-level intensity for the most recent inventory cycle. For each species, we calculated a centroid of each species' current range following Fei et al. (2017) by weighting the latitude and longitude of each plot by the relative basal area of each species in each plot and taking the average across all plots where the species was present. We repeated this process for trees that were corrected using the earliest recorded SPCD and compared the two centroids. Second, we calculated species richness for FIA plots with at least one tree with a SPCD change. We compared plot-level species richness using the most recent SPCD versus the earliest SPCD for all live trees. Third, we evaluated differences in carbon stock estimates using the two SPCD correction scenarios. The FIA program recently released updated national-scale volume and biomass models (NSVB) (Westfall et al., 2023). NSVB simplifies tree-level volume, biomass, and carbon estimation into four main model forms with coefficients and carbon fractions that vary by species, region (i.e., eco-subdivision, Cleland et al., 2007), and stand origin (i.e., natural or planted forest) (Westfall et al., 2023). In some cases, species may share the same model form, coefficients, and/or carbon fractions (usually when in the same genus or family); other times, they may differ. We compared individual tree-level carbon stock estimates under the two correction scenarios. We also calculated population estimates of aboveground live carbon stocks per unit area for the state of Missouri, where a high level of SPCD mismatches occurred, using aboveground carbon estimates for live trees with SPCD corrected under the two scenarios. All analyses were conducted in R (R Core Team, 2023, Version 4.3.1), using the “odbc” (Hester et al., 2024) and “RSQLite” (Müller et al., 2023) packages for querying FIA data and the “rFIA” package for carbon estimation (Stanke et al., 2020). R code for querying the FIA database and linking trees through time and the output table of tree remeasurements is available through the Purdue University Research Repository (Knott et al., 2025; <https://purr.purdue.edu/publications/4808/1>).

RESULTS

We linked remeasurements of approximately 3.4 million unique live trees (accounting for approximately 9.6

million out of 12.3 million total live tree records from the annualized FIA inventory). These trees have been measured two times (1,819,002), three times (742,684), four times (666,733), five times (206,649), and six times (10,170). The remaining 2,624,843 live trees were only measured once or were only alive at one measurement. We found 114,213 unique trees that had their SPCD change at least once (2.8% of unique trees), and 98,164 of these trees are included in base intensity FIA plots of the current inventory cycle (41,777 plots with at least one tree with a SPCD change) (Figure 1). When grouped into sapling and tree size classes (12.7 cm dbh threshold based on FIA sampling design), trees with

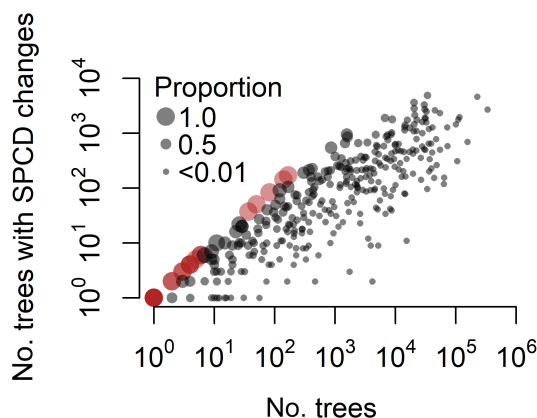


FIGURE 1 Number of remeasured trees with mismatches of species identification code (SPCD). Each point represents a species that had at least one tree with a species code change between remeasurements. Size varies by proportion of remeasured live trees with at least one mismatch. Points in red indicate species where all remeasured trees had a species code change; note that these species were systematic SPCD changes to the FIA species list.

SPCD mismatches occurred at a higher proportion in the smaller sapling size class than expected based on the proportion of trees in the smaller size class without mismatches (0.212 vs. 0.176 proportion of trees <12.7 cm dbh for SPCD mismatched trees vs. non-mismatched trees, χ^2 test, $\chi^2 = 1064.1$, $df = 1$, $p < 0.0001$).

Areas of higher mismatch rates were found in the eastern United States with hotspots in southern Missouri and Georgia (Figure 2). Range centroids for species with >1000 trees with SPCD changes over the course of the annualized inventory ($n = 33$ species) reflected this spatial pattern. Current species' centroids calculated using trees corrected using the first recorded SPCD were more often southward from the species' current centroid calculated using most recently recorded SPCD ($n = 20$ south, 13 north, mean latitude difference = -3.8 km, $t = -2.94$, $df = 32$, $p = 0.006$; Figure 3a). An approximately equal number of species had eastward ($n = 15$ species) versus westward ($n = 18$) differences in centroids between the two correction scenarios (mean longitude difference = 0.3 km, $t = 0.19$, $df = 32$, $p = 0.848$; Figure 3a). Total distance between centroids ranged from 0.3 to 24.5 km (Figure 3b).

Species richness of current inventory plots that had at least one tree with a SPCD change varied from 1 to 20 species using the current SPCD and 1 to 19 using the first recorded SPCD (Figure 4a). In total, 24,262 out of 41,777 plots (58.1%) had the same richness under the two correction scenarios. The remaining plots had ± 4 species difference in richness between the two correction scenarios (Figure 4b). Although it seems logical that a larger quantity of SPCD changes would occur in plots with higher species richness (i.e., a larger species pool that the field crews would need to be familiar

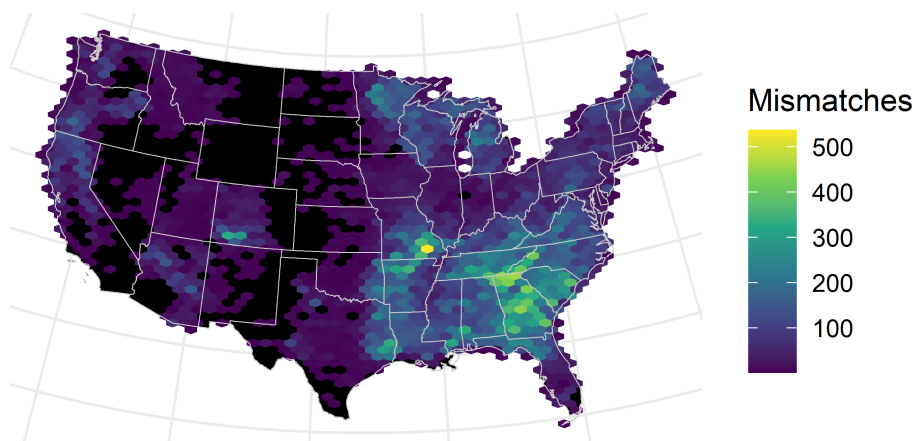


FIGURE 2 Hexagon heat map of species identification code (SPCD) mismatch frequencies (number of stems) included in the current cycle of the annual inventory. Locations (based on perturbed Forest Inventory and Analysis Program [FIA] plot coordinates) and hexagon size defined arbitrarily for visualization purposes only.

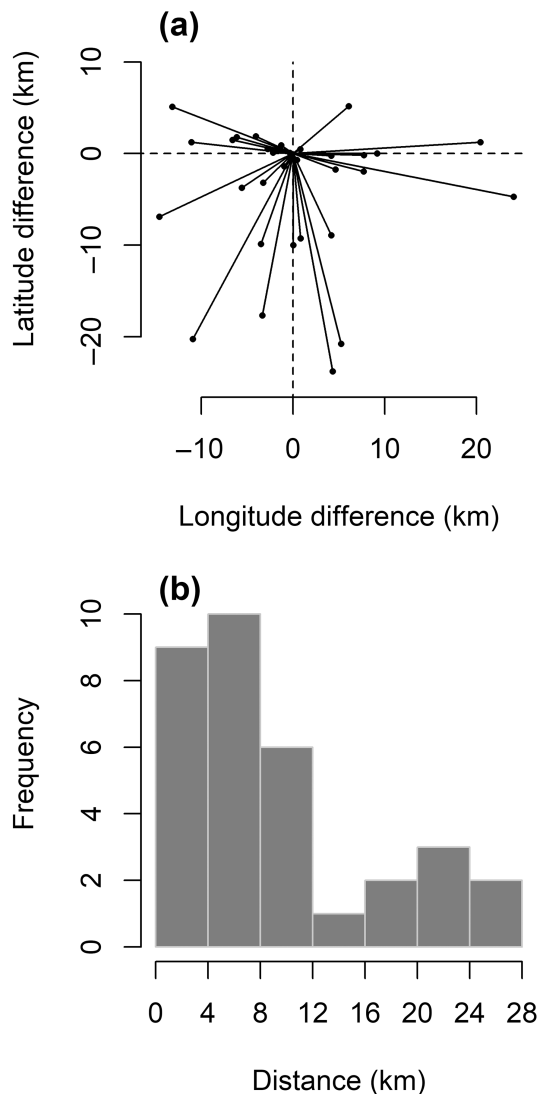


FIGURE 3 Difference in current species range centroids between species correction scenarios. Centroids were calculated based on relative basal area-weighted latitude and longitude of current inventory plots for species with at least 1000 trees with species identification code (SPCD) changes. (a) Difference between centroids between correction scenarios. Arrows are centered on the species centroid using the current SPCD. (b) Histogram of distances between centroids.

with), there was a negligible correlation between these two variables ($r = 0.08$).

Although most trees with a SPCD change had a different carbon stock estimate between the two correction scenarios (91.4%), tree-level carbon stock estimates were highly correlated ($r = 0.987$, $t = 1855.6$, $df = 91,830$, $p < 0.001$; Figure 5a). The differences were usually small and on average not significantly different than zero (mean = 0.77 kg, $t = 1.78$, $df = 91,830$, $p = 0.07$), with half of the first SPCD corrected trees carbon stock estimates falling within

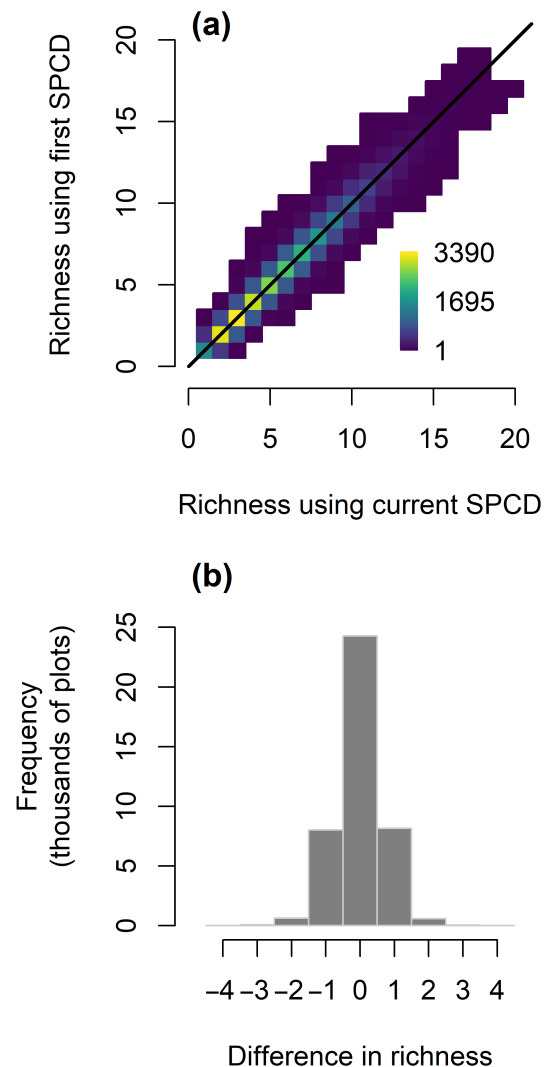


FIGURE 4 Species richness of Forest Inventory and Analysis Program (FIA) plots in the most recent inventory with at least one tree with a species identification code (SPCD) change using current or first recorded SPCD of trees in the plot. (a) Relationship between species richness under the two correction scenarios. (b) Frequency of differences in species richness using the two correction scenarios (current minus first SPCD).

−6.6% to +6.7% of the current SPCD corrected trees carbon stock estimates (Figure 5b). A total of 1761 trees (1.6%) had large differences between the correction scenarios (>50% absolute difference). When expanded to the population level for the state of Missouri, where the largest quantity of SPCD changes occurred, carbon density estimates (i.e., carbon stocks per unit area) were nearly identical (25.47 vs. 25.45 Mg ha^{−1} for current and first SPCD, respectively, 0.07% difference). This is, in part, due to the small quantity of trees with SPCD changes relative to the total number of trees used for the population estimation (10,217 out of 186,193 trees in Missouri had SPCD changes, 5.48%).

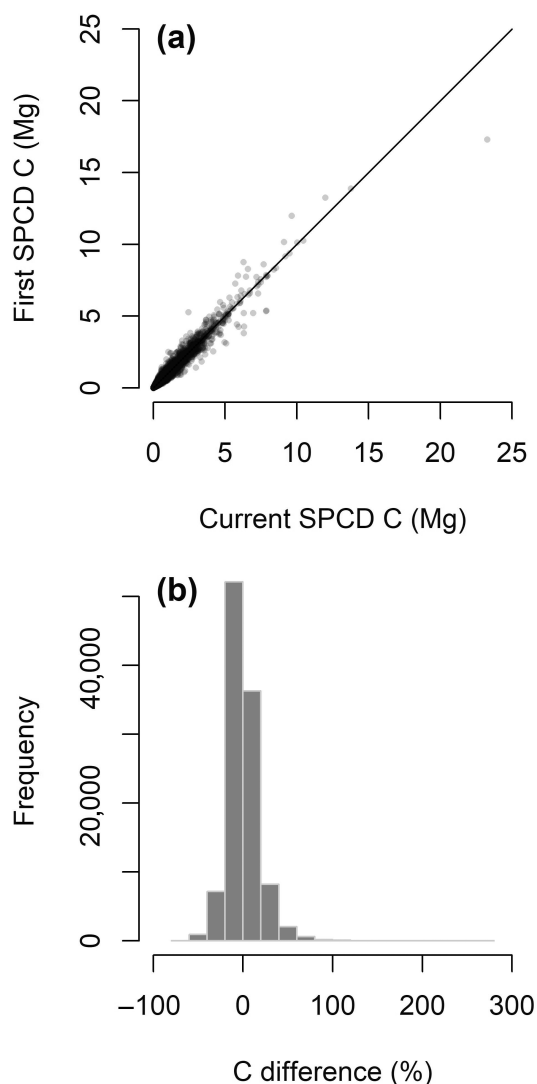


FIGURE 5 Differences in tree-level carbon (C) estimates using the two correction scenarios. (a) Amount of carbon for individual trees using the current versus first recorded species identification code (SPCD). Black line indicates 1:1 relationship. (b) Percent difference between individual tree carbon estimates using current versus first recorded SPCD.

DISCUSSION

Our analysis linked individual trees between remeasurements of FIA plots to reveal changes in SPCDs over time. Our results illustrated that correcting SPCDs had mixed impacts across scales: on an individual tree level, live aboveground carbon stocks varied from -72.4% to $+269.9\%$ between the two correction scenarios, but on average differences in tree-level carbon stocks were not significantly different from zero. At the species level, range centroids were sensitive to SPCD changes, with ranges more southward when using earlier SPCDs because of the higher SPCD change rates in the

southeastern United States. Differences in current centroids of approximately 25 km would equate to ± 1.25 km per year or more shift rates attributed only to the choice of SPCD correction, in addition to true shifts due to species migrations in response to climate change (Fei et al., 2017; Zhu et al., 2012). At the community level, species richness was frequently the same under the correction scenarios but varied up to ± 4 species. Finally, at the population level, an estimate of aboveground live tree carbon density for the state of Missouri, where many SPCD changes occurred, was robust to SPCD changes because of the relatively small quantity of trees with SPCD changes relative to those with stable SPCDs. This was reassuring to find, as the US GHG inventory relies on FIA-based forest carbon estimates (Domke et al., 2023; US EPA, 2024).

In the context of large-scale datasets like FIA, species misidentifications can arise from a variety of causes. These include observer error, where field crews for one remeasurement may differ in experience or familiarity with a certain species than previous crews and therefore are more or less likely change the SPCD of a tree (Morrison, 2016). Some mismatches in the FIA database can be attributed to programmatic changes in the FIA species list (appendix 14 in USDA Forest Service, 2023). The largest changes occurred when FIA switched from periodic to annual inventories in the late 1990s/early 2000s and in 2019/2020 when FIA regional species lists were merged into one national species list. We found a few species (highlighted in red in Figure 1) where all trees were reassigned to a new SPCD; these are likely the result of programmatic changes in species lists.

Species with similar characteristics that have overlapping distributions may be difficult to distinguish and therefore have a large quantity of SPCD changes. For example, northern red oak (*Quercus rubra*, SPCD 833, $N = 2586$) and black oak (*Quercus velutina*, SPCD 837, $N = 3266$); pignut hickory (*Carya glabra*, SPCD 403, $N = 3587$) and mockernut hickory (*Carya alba*, SPCD 409, $N = 2802$); and white ash (*Fraxinus americana*, SPCD 541, $N = 1844$) and green ash (*Fraxinus pennsylvanica*, SPCD 544, $N = 4870$) were all common SPCD changes within their overlapping ranges and are morphologically similar, especially during leaf-off seasons (Burns & Honkala, 1990). Small trees had more frequent SPCD changes, supporting the notion that larger, older trees tend to be easier to identify. It is also possible that some small trees were not misidentified but rather were truly different trees that were falsely linked via PREV_TRE_CN in the FIA database, for example, when a sapling dies between remeasurements, and a new sapling of a different species grows to a similar size at the same location.

We applied two simple species identification correction methods to our remeasured tree data, but there are more complex methods that could be applied. Trees that have been measured three or more times could use the most frequently applied species code. Other plot-level characteristics could be used to assign the likelihood of a misidentified species being another species. For example, there is higher confidence in a true misidentification when a SPCD changed from white ash to green ash in a green ash-dominated plot, but there is lower confidence in a similar SPCD change in a plot containing both ash species. Misidentification rates (i.e., the frequency that one SPCD changes to another) could be applied to singly measured trees to randomly select a subset of trees to be reclassified as a different species. Removing questionable data (e.g., removing trees or plots with species code changes) can potentially break the assumptions of a probability-based sample, mimicking larger rates of nonresponse that may be spatially clustered (Westfall et al., 2022).

Our aim was not to have a comprehensive analysis or provide the best solution for the SPCD mismatch issue, but rather to bring attention to this nuance in the FIA database and to provide examples of how common data correction techniques (i.e., keeping the earliest or most recent SPCD) may lead to differing outcomes. This nuance in the data may influence other topics of interest beyond species richness, range dynamics, and carbon, such as quantifying shifts in community composition (Knott et al., 2020, 2022), classifying forests as mature and old growth (Barnett et al., 2023; Gray et al., 2023), understanding invasion patterns and biotic resistance (Iannone et al., 2016; Oswalt et al., 2015), and assessing stand dynamics like disturbance, mortality, regeneration, and recruitment (Fei et al., 2019; Harris et al., 2022; Lines et al., 2022; Lintz et al., 2016), among others. Our study highlights the potential impacts of blindness toward the underlying data (e.g., the reliance of carbon attributes in the FIA database on species identification) of species-level information obtained from FIA data.

The FIA program is national in scope, overseen at the regional level, with collection occurring at the state level (Bechtold & Patterson, 2005; Renwick, 2023). As such, decisions to keep or change protocols and data structure take considerable time and coordination by FIA leadership and staff. Therefore, the burden falls on data users in the interim to ensure proper use of the data until programmatic changes occur. Furthermore, studies that do not consider the effects of decisions made about the inclusion, exclusion, or correction of FIA data may draw improper conclusions about status and trends in forest resources.

AUTHOR CONTRIBUTIONS

Conceptualization: Jonathan Knott, Jianmin Wang, Grant Domke, and Songlin Fei. *Data curation:* Jonathan Knott. *Formal analysis:* Jonathan Knott, Jianmin Wang, and David Walker. *Methodology:* Jonathan Knott, Jianmin Wang, and Grant Domke. *Writing—original draft:* Jonathan Knott. *Writing—review and editing:* Jonathan Knott, Jianmin Wang, David Walker, Grant Domke, and Songlin Fei.

ACKNOWLEDGMENTS

We thank the numerous field crew members who have collected FIA data over the years. We also thank FIA staff members, including Brian Walters, Brian Gasper, Jim Westfall, and Scott Pugh, for insights into data collection and data analysis practices. This project was supported by the USDA Forest Service, Northern Research Station, Forest Inventory and Analysis Program. The findings and conclusions in this publication are solely those of the authors and should not be construed to represent any official USDA or US Government determination or policy.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data are available in a variety of formats from the FIA DataMart: <https://apps.fs.usda.gov/fia/datamart/datamart.html>. R code (Knott et al., 2025) for querying the FIA database and linking individual tree remeasurements through time, and the output table of tree remeasurements are available from the Purdue University Research Repository: <https://purr.purdue.edu/publications/4808/1>.

ORCID

Jonathan Knott  <https://orcid.org/0000-0003-3856-8454>

Jianmin Wang  <https://orcid.org/0000-0001-6739-9499>

David Walker  <https://orcid.org/0000-0003-2048-3217>

Grant Domke  <https://orcid.org/0000-0003-0485-0355>

Songlin Fei  <https://orcid.org/0000-0003-2772-0166>

REFERENCES

- Barnett, K., G. H. Aplet, and R. T. Belote. 2023. "Classifying, Inventorying, and Mapping Mature and Old-Growth Forests in the United States." *Frontiers in Forests and Global Change* 5: 25. <https://doi.org/10.3389/ffgc.2022.1070372>.
- Bechtold, W. A., and P. L. Patterson. 2005. "The Enhanced Forest Inventory and Analysis Program—National Sampling Design and Estimation Procedures." 80. USDA Forest Service, Southern Research Station. <https://doi.org/10.2737/SRS-GTR-80>.
- Burns, R. M., and B. H. Honkala. 1990. *Silvics of North America: Volume 2. Hardwoods* 654. Washington, DC: USDA Forest Service. Agriculture Handbook.

- Cleland, D. T., J. A. Freeouf, J. E. J. Keys, G. J. Nowacki, C. A. Carpenter, and W. H. McNab. 2007. "Ecological Subregions: Sections and Subsections for the Conterminous United States." General Technical Report WO-76D 76. <https://doi.org/10.2737/WO-GTR-76D>.
- Costa, H., G. M. Foody, S. Jiménez, and L. Silva. 2015. "Impacts of Species Misidentification on Species Distribution Modeling with Presence-Only Data." *ISPRS International Journal of Geo-Information* 4(4): 2496–2518. <https://doi.org/10.3390/ijgi4042496>.
- Domke, G. M., B. F. Walters, C. L. Giebink, E. J. Greenfield, J. E. Smith, M. C. Nichols, J. A. Knott, S. M. Ogle, J. W. Coulston, and J. Steller. 2023. *Greenhouse Gas Emissions and Removals from Forest Land, Woodlands, Urban Trees, and Harvested Wood Products in the United States, 1990–2021*. Resource Bulletin WO-101. Washington, DC: USDA Forest Service. <https://doi.org/10.2737/WO-RB-101>.
- Domke, G. M., C. W. Woodall, B. F. Walters, R. E. McRoberts, and M. A. Hatfield. 2014. "Strategies to Compensate for the Effects of Nonresponse on Forest Carbon Baseline Estimates from the National Forest Inventory of the United States." *Forest Ecology and Management* 315: 112–120. <https://doi.org/10.1016/j.foreco.2013.12.031>.
- Fei, S., J. M. Desprez, K. M. Potter, I. Jo, J. A. Knott, and C. M. Oswalt. 2017. "Divergence of Species Responses to Climate Change." *Science Advances* 3(5): e1603055. <https://doi.org/10.1126/sciadv.1603055>.
- Fei, S., R. S. Morin, C. M. Oswalt, and A. M. Liebhold. 2019. "Biomass Losses Resulting from Insect and Disease Invasions in US Forests." *Proceedings of the National Academy of Sciences of the United States of America* 116(35): 17371–76. <https://doi.org/10.1073/pnas.1820601116>.
- Fei, S., and K. C. Steiner. 2007. "Evidence for Increasing Red Maple Abundance in the Eastern United States." *Forest Science* 53(4): 473–77. <https://doi.org/10.1093/forestscience/53.4.473>.
- Gray, A. N., K. Pelz, G. D. Hayward, T. Schuler, W. Salverson, M. Palmer, C. Schumacher, and C. W. Woodall. 2023. "Perspectives: The Wicked Problem of Defining and Inventorying Mature and Old-Growth Forests." *Forest Ecology and Management* 546: 121350. <https://doi.org/10.1016/j.foreco.2023.121350>.
- Harris, L. B., C. W. Woodall, and A. W. D'Amato. 2022. "Increasing the Utility of Tree Regeneration Inventories: Linking Seedling Abundance to Sapling Recruitment." *Ecological Indicators* 145(December): 109654. <https://doi.org/10.1016/j.ecolind.2022.109654>.
- Hester, J., H. Wickham, and O. Gjoneski. 2024. "odbc: Connect to ODBC Compatible Databases (Using the DBI Interface)." <https://CRAN.R-project.org/package=odbc>.
- Iannone, B. V., K. M. Potter, K. D. Hamil, W. Huang, H. Zhang, Q. Guo, C. M. Oswalt, C. W. Woodall, and S. Fei. 2016. "Evidence of Biotic Resistance to Invasions in Forests of the Eastern USA." *Landscape Ecology* 31(1): 85–99. <https://doi.org/10.1007/s10980-015-0280-7>.
- IPCC. 2019. "2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories." Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/>.
- Knott, J., G. Domke, C. Woodall, B. Walters, M. Jenkins, and S. Fei. 2022. "Shifting Forests and Carbon: Linking Community Composition and Aboveground Carbon Attributes." *Ecosystems* 26: 412–427. <https://doi.org/10.1007/s10021-022-00765-6>.
- Knott, J., J. Wang, D. Walker, G. Domke, and S. Fei. 2025. *FIA Tree Species Code Changes through Time*. West Lafayette, IN: Purdue University Research Repository. <https://doi.org/10.4231/0E48-T344>.
- Knott, J. A., M. A. Jenkins, C. M. Oswalt, and S. Fei. 2020. "Community-Level Responses to Climate Change in Forests of the Eastern United States." *Global Ecology and Biogeography* 29(8): 1299–1314. <https://doi.org/10.1111/geb.13102>.
- Knott, J. A., G. C. Liknes, C. L. Giebink, S. Oh, G. M. Domke, R. E. McRoberts, V. F. Quirino, and B. F. Walters. 2023. "Effects of Outliers on Remote Sensing-Assisted Forest Biomass Estimation: A Case Study from the United States National Forest Inventory." *Methods in Ecology and Evolution* 14: 1587–1602. <https://doi.org/10.1111/2041-210X.14084>.
- Lines, E. R., F. J. Fischer, H. J. Foord Owen, and T. Jucker. 2022. "The Shape of Trees: Reimagining Forest Ecology in Three Dimensions with Remote Sensing." *Journal of Ecology* 110(8): 1730–45. <https://doi.org/10.1111/1365-2745.13944>.
- Lintz, H. E., A. N. Gray, A. Yost, R. Snieszko, C. Woodall, M. Reilly, K. Hutten, and M. Elliott. 2016. "Quantifying Density-Independent Mortality of Temperate Tree Species." *Ecological Indicators* 66(July): 1–9. <https://doi.org/10.1016/j.ecolind.2015.11.011>.
- Morrison, L. W. 2016. "Observer Error in Vegetation Surveys: A Review." *Journal of Plant Ecology* 9(4): 367–379. <https://doi.org/10.1093/jpe/rtv077>.
- Müller, K., H. Wickham, D. A. James, and S. Falcon. 2023. "RSQLite: SQLite Interface for R." R Package Version 2.3.1. <https://CRAN.R-project.org/package=RSQLite>.
- Oswalt, C. M., S. Fei, Q. Guo, B. V. Iannone, III, S. N. Oswalt, B. C. Pijanowski, and K. M. Potter. 2015. "A Subcontinental View of Forest Plant Invasions." *NeoBiota* 24: 49–54. <https://doi.org/10.3897/neobiota.24.4526>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.
- Renwick, K. 2023. "Forest Inventory and Analysis, Fiscal Year 2022 Business Report." FS-1230. USDA Forest Service. <https://research.fs.usda.gov/understory/2022-forest-inventory-and-analysis-business-report>.
- Rodrigues, A. V., G. Nakamura, G. Staggemeier, and L. Duarte. 2022. "Species Misidentification Affects Biodiversity Metrics: Dealing with this Issue Using the New R Package naturaList." *Ecological Informatics* 69(July): 101625. <https://doi.org/10.1016/j.ecoinf.2022.101625>.
- Stanke, H., A. O. Finley, A. S. Weed, B. F. Walters, and G. M. Domke. 2020. "rFIA: An R Package for Estimation of Forest Attributes with the US Forest Inventory and Analysis Database." *Environmental Modelling & Software* 127(May): 104664. <https://doi.org/10.1016/j.envsoft.2020.104664>.
- Tinkham, W. T., P. R. Mahoney, A. T. Hudak, G. M. Domke, M. J. Falkowski, C. W. Woodall, and A. M. S. Smith. 2018. "Applications of the United States Forest Inventory and Analysis Dataset: A Review and Future Directions." *Canadian*

- Journal of Forest Research* 48(11): 1251–68. <https://doi.org/10.1139/cjfr-2018-0196>.
- Tomppo, E., T. Gschwantner, M. Lawrence, R. E. McRoberts, K. Gabler, K. Schadauer, C. Vidal, A. Lanz, G. Ståhl, and E. Cienciala. 2010. *National Forest Inventories: Pathways for Common Reporting*, Vol. 1. Dordrecht, The Netherlands: Springer. <https://doi.org/10.1007/978-90-481-3233-1>.
- US EPA. 2024. “Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2022.” EPA 430-R-24-004. US Environmental Protection Agency. <https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2022>.
- USDA Forest Service. 2023. “Forest Inventory and Analysis National Core Field Guide for the Nationwide Forest Inventory.” USDA Forest Service. <https://research.fs.usda.gov/understory/nationwide-forest-inventory-field-guide>.
- Westfall, J. A., J. W. Coulston, A. N. Gray, J. D. Shaw, P. J. Radtke, D. M. Walker, A. R. Weiskittel, et al. 2023. *A National-Scale Tree Volume, Biomass, and Carbon Modeling System for the United States*. WO-GTR-104. Washington, DC: U.S. Department of Agriculture, Forest Service. <https://doi.org/10.2737/WO-GTR-104>.
- Westfall, J. A., T. A. Schroeder, J. M. McCollum, and P. L. Patterson. 2022. “A Spatial and Temporal Assessment of Nonresponse in the National Forest Inventory of the U.S.” *Environmental Monitoring and Assessment* 194(8): 530. <https://doi.org/10.1007/s10661-022-10219-0>.
- Yanai, R. D., A. R. Young, J. L. Campbell, J. A. Westfall, C. J. Barnett, G. A. Dillon, M. B. Green, and C. W. Woodall. 2023. “Measurement Uncertainty in a National Forest Inventory: Results from the Northern Region of the USA.” *Canadian Journal of Forest Research* 53(3): 163–177. <https://doi.org/10.1139/cjfr-2022-0062>.
- Zhu, K., C. W. Woodall, and J. S. Clark. 2012. “Failure to Migrate: Lack of Tree Range Expansion in Response to Climate Change.” *Global Change Biology* 18(3): 1042–52. <https://doi.org/10.1111/j.1365-2486.2011.02571.x>.

How to cite this article: Knott, Jonathan, Jianmin Wang, David Walker, Grant Domke, and Songlin Fei. 2025. “Robustness of Ecological Indicators to Species Misidentification in the National Forest Inventory of the United States.” *Ecosphere* 16(7): e70340. <https://doi.org/10.1002/ecs2.70340>