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Research Article

Forest conversions in the United States from a certification and regulatory perspective

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Abstract

Forest conversions are an important consideration of the forest products sector. Both third-party certifications, such as the Sustainable Forestry Initiative, and government regulation, such as the European Union Regulation on Deforestation Free Supply Chains, require knowledge of conversions in fiber supply regions. Here we develop a new approach to estimate some relevant forest conversion metrics for economic regions of the United States. Across economic regions, forest conversion rates were small. For example, gross annual forest loss to agriculture was <0.044%, gross annual natural forest loss to planted forest was <0.86%, net annual loss in natural forest was <0.41%, and net 10-year forest loss was <1.86%. Our results suggest three major conclusions. First, forest conversions to agriculture are not currently an issue in roundwood producing regions of the United States. Second, natural forest conversions to planted forest are offset by landowners choosing to use natural regeneration methods. Third, there are several economic regions where 10-year net forest loss approaches but does not exceed 1% net loss at $p = 0.95$. Finer-scale analyses, in these economic regions, will likely be necessary for the forest products sector to ensure compliance with forest certification standards.

Key words: sustainability, markets, markov process, land use change, forest conditions

Introduction

Increasing concerns around forest sustainability and transparency within the forest products sector over the last 30 years have led to several forest certification bodies that offer third party verification of ecological, economic, and social sustainability principles (Garzon et al. 2020). The intent behind certification is to provide assurances that forests are managed to provide a suite of ecosystem services in perpetuity (Van Deusen and Roesch 2009). One element typically found among third party certification standards is forest conversion. Forest conversion is also an element of some governmental regulations (e.g., European Union Regulation on Deforestation Free Supply Chains; EUDR). For our purposes, we define forest conversion as human choices that change forest land use to non-forest land uses or natural forest land uses to a planted forest land use. Our focus is on quantifying forest conversion metrics in the United States that are relevant to select forest certifications (Sustainable Forestry Initiative and Forest Stewardship Council) and regulations (EUDR). While we quantify the forest conversion metrics for broad geographic regions of the United States, we intend for our new estimation approach to be used by practitioners for fiber supply regions at least 0.5 million ha in extent.

Indicators and measures of forest conversion have understandably changed over time. As monitoring techniques improve, data streams advance, and public perceptions shift, both governmental and non-governmental approaches to assess rates of forest conversion will undoubtedly change. The EUDR offers one example (EU 2023/1115). This regulation strives to curb deforestation by ensuring suppliers document that forest and agricultural products sold in the European Union do not arise from forest conversion to agriculture. Further, EUDR differentiates between natural forest and planted forest, such that converting natural forests to planted forest (considered “degradation” in the regulation) is also an issue with respect to their criterion. The regulation requires substantial documentation from suppliers of agricultural and forest products selling in the European Union, including reporting geographic coordinates (or polygons) for all land areas contributing raw material to the final products.

In the United States, third-party forest certification standards including the American Tree Farm System (ATFS)®, Sustainable Forestry Initiative (SFI)®, and Forest Stewardship

Council (FSC)® are key programs the forest products sector relies on to ensure sustainable forest management and fiber sourcing. For corporate forest owners, the SFI and FSC standards require certified organizations who manage forestland and entities who source fiber to adhere to a common set of principles to manage risk. These principles include reducing conversion of forests, limiting sourcing of fiber from "controversial sources," protecting high conservation value forests, and protection of water resources and biodiversity.

Like the EUDR, natural forest conversion to planted forest is also a component of Forest Stewardship Council certification (Garzon et al. 2020). The FSC Controlled Wood Standard for the United States (Forest Stewardship Council 2017) describes requirements for companies that purchase wood as a raw material to be used in an FSC-certified product. The FSC standard considers "wood from forests being converted to plantations or non-forest use" as coming from "unacceptable sources". The FSC standard states that forest supply areas can be considered low risk if "There is no net loss or no significant rate of loss (>0.5% per year) of natural forests," Therefore, certificate holders must document rates of natural forest loss in their supply areas.

The SFI fiber sourcing standard requires a certified organization to, "manage the risk of sourcing fiber from controversial sources". Controversial sources are defined broadly in the 2022 SFI standard but include "sources originating from regions experiencing forest area decline". While defining a region is at the discretion of a Certified Organization, SFI considers regions "with a net loss of forest area <1% over the most recent 10 years of available data" to be low risk. Conversely, areas with higher forest conversion rates are deemed high risk and, therefore, fiber sourced from areas of high risk is treated as controversial sources (SFI 2023).

The SFI standard also designates specific public data sources to identify potential controversial regions. In the United States, data arising from the National Forest Inventory (NFI; Bechtold and Patterson 2005; Westfall et al. 2022), collected through the United States Forest Service, Forest Inventory and Analysis (FIA) program are specifically recognized. Van Deusen and Roesch (2009) developed a weighted maximum likelihood estimator to estimate conversion rates using United States NFI data. Roesch and Van Deusen (2012) compared the weighted maximum likelihood estimator to design-based approaches used with NFI data in the United States. Roesch and Van Deusen (2012) note that bias was potentially unimportant when conversion rates were small, and results indicated small conversion rates for 12 U.S. states (e.g., annual forest converstion to non-forest between 0.4% and 0.8% annually). Renwick et al. (2025) also used United States NFI data to specifically examine forest to agriculture conversions. They found that in the United States, annual conversion of forest to agriculture was less than 0.04%. One key contribution of these papers was demonstrating the use of NFI data to construct estimates of conversion rates. Additionally, Van Deusen and Roesch (2009) and Roesch and Van Deusen (2012) present the standard error of conversion rate estimates. There is a logical extension of the estimator presented by Van Deusen and Roesch (2009). Their approach creates a binomial indicator variable from plot-level forest conversion observations and hence is a binomial random variable arising from a binomial process. Given that a binomial process is a special case of a Markov process or Markov chain, the approach of Van Deusen and Roesch (2009) can be extended to a Markov chain which is commonly used in land use change analysis and modelling (Iacono et al. 2015).

There are remote sensing-based approaches applicable to estimating forest conversion. Homer et al. (2020), Fitts et al. (2021), and Arevalo et al. (2020) offer some recent examples of remote sensing-based approaches in the United States, Minnesota, and Columbian Amazon, respectively. Homer et al. (2020) results suggest that from 2001 to 2016 the average annual net loss of forest was 0.21% for the conterminous United States. Yet, there remains significant challenges from both a definitional perspective and from an error propagation perspective. Often remote sensing-based approaches rely on cover-based land definitions which is different from land use, particularly for forests (Coulston et al. 2014). These definitional differences can impact assessments of forest conversion rates and net forest change. For example, forests that have been recently harvested and are in the early stages of natural regeneration would generally be considered a forest conversion to a non-forest cover under land cover-based approaches. Challenges also arise because remotely sensed-based maps are typically derived from a series of models that translate at-sensor reflectance to surface reflectance, which is used as an input to land cover models (Khorram et al. 2016). As such, areal extent of land classes calculated by counting pixels will be biased (Stehman 2000, 2012). Arevalo et al. (2020) overcame this issue by employing a sample-based approach to correct model bias and provide estimates of conversions and associated estimates of precision.

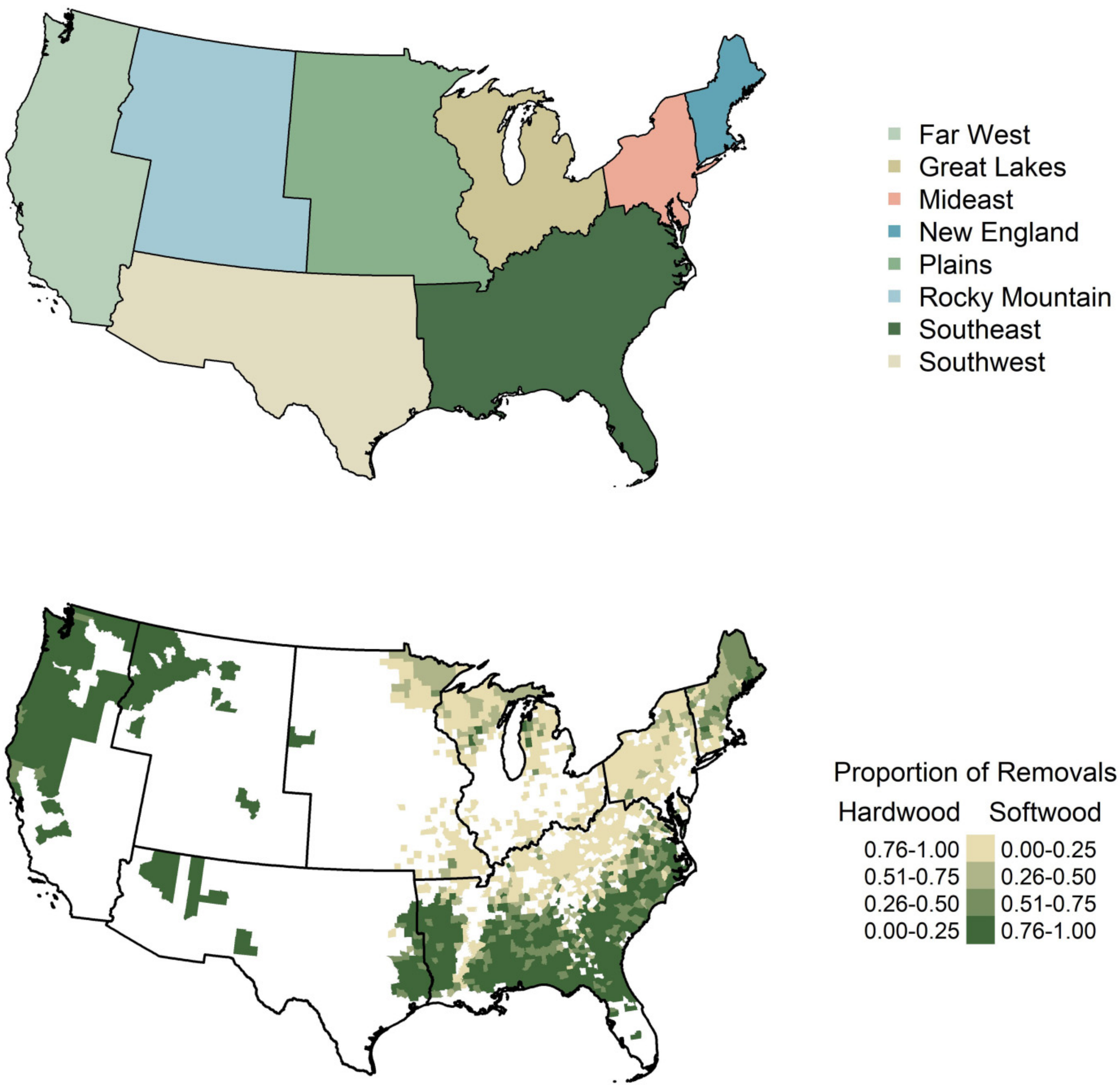
There is a need to estimate and monitor forest land use conversion rates relevant to certifications and regulations, at spatial scales ranging from fiber supply regions for individual mills to national-scales, and temporal scale from annual to decadal. Further, short-term projections can help procurement foresters to anticipate whether their supply region may be classified as a "controversial source" (SFI 2023) in the future given increases in forest to non-forest conversion. Here we develop and use an NFI-based approach to estimate EUDR, FSC, and SFI forest conversion metrics and standard errors. Our approach can be considered a Markov chain approach designed to estimate a range of forest conversion metrics. Using the most recent United States NFI data, we estimate gross annual forest conversion to agriculture (EUDR metric) and gross annual natural forest conversion to planted forest (EUDR metric). We also estimate annual net change in natural forest (FSC metric), 10-year net forest change rates (SFI metric), and offer short-term projections for 10-year net forest change rates. We present estimates for eight broad economic regions of the United States.

Methods

Study area

Our study area is the conterminous United States. We estimate forest conversion ratess for areas likely to be a source of

Fig. 1. United States Department of Commerce, Bureau of Economic Analysis regions (top panel) and selected locations (counties) which account for 95% of total annual softwood and hardwood removals and 97% of total annual removals (bottom panel) in the United States (Tables 1 and 2). In the bottom panel, each county is shaded based on the share of average annual hardwood and softwood removals in each county (see Table 2 for data collection years). Figure was created using R 4.1.1 and assembled using data from the U.S. Bureau of Economic Analysis (2024) and the United States NFI available at https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart.



roundwood for forest products in each Bureau of Economic Analysis region (BEA, U.S. Bureau of Economic Analysis 2024, Fig. 1, Table 1). Because EUDR, FSC, and SFI forest conversion metrics are focused on products from roundwood arising from controversial sources, we limit our analysis to subregional areas (counties that reflect roundwood supply; Fig. 1, Table 2). Publicly owned and privately owned land in these counties are included regardless of protected status.

Forest removals (i.e., removal of growing stock trees > 12.7 cm by cutting) can occur for several reasons including harvest for products, land use change, timber stand improvement, and invasive species eradication. To select counties (administrative divisions of each state) that reflect roundwood supply, we sorted the most current (see Table 2 for time period for each region) county-level average annual softwood removal estimates in descending order, calculated the cumulative proportion of total U.S. average annual softwood removals for each county, and selected the set of counties that accounted for 95% of total U.S. average annual softwood removals. We followed the same procedure for average annual hardwood removals. If a county was selected because of either its softwood removal volume or its hardwood removal volume, it was retained for analysis. The set of selected counties accounted for 97.3% of all removals in the U.S. and were assumed to be likely areas to contribute to roundwood supply.

Based on United States NFI data most of 275 million ha of forest land in the BEA regions were privately owned (Table 1).

Table 1. Summary statistics for each Bureau of Economic Analysis region.

BEA region	Total forest area (million ha)	Average annual removals (million m^3 $year^{-1}$)	Public forest (%)	Private forest (%)	Number of mills	Number of certified mills
Far West	38	68.9	65	35	181	93
Great Lakes	22	31.7	29	71	139	48
Mideast	16	17.9	30	70	91	27
New England	13	19.6	17	83	74	26
Plains	17	13.4	34	66	50	8
Rocky Mountain	40	12.4	79	21	48	19
Southeast	82	236.0	16	84	707	301
Southwest	46	17.8	27	73	65	23
Total	275	417.7			1355	545

Note: Mill information was obtained from Forisk (2023). All other information is from the United States NFI. Data collection years for United States NFI are identified in Table 2. NFI, National Forest Inventory.

Table 2. Summary statistics for selected counties within each Bureau of Economic Analysis region.

BEA region	Sample plots (n)	Forest area (million ha)	Planted forest (%)	Average annual hardwood removals (million m^3 $year^{-1}$)	Average annual softwood removals (million m^3 $year^{-1}$)	Measurement years	Remeasurement years
Far West	15 984	28	19	4.9	63.3	2000–2011	2011–2021
Great Lakes	11 854	17	7	23.8	5.8	2008–2014	2014–2022
Mideast	7418	13	4	15.4	1.8	2009–2014	2015–2022
New England	5970	12	2	9.6	9.9	2009–2015	2015–2023
Plains	8501	11	5	9.7	2.6	2008–2015	2015–2021
Rocky Mountain	4667	12	2	0.1	10.9	2002–2012	2012–2019
Southeast	42 400	68	29	64.7	167.8	2011–2017	2017–2023
Southwest	6735	10	26	2.4	14.0	2001–2011	2011–2022
Total	103 529	170		130.6	276.1		

In 2023, 40% of the 1355 mills operating in the conterminous United States were certified to the fiber sourcing requirements of the SFI and/or FSC standards (Forisk 2023). The Southeast BEA region had the largest areal extent and about 83% of its forest area was selected as part of our analysis (Table 2). In addition, the Southeast had the largest amount of both annual average hardwood and softwood removals (Table 2). The Far West and Great Lakes regions had the second largest amount of annual average softwood and hardwood removals, respectively. The Rocky Mountain region had the smallest amount of average annual removals. Sample size varied proportional to the combined area of selected counties in each region and ranged from 5970 sample plots in the New England region to 42 400 in the Southeast region.

Data

The United States NFI serves as the basis for our analysis. The sampling design and associated design-based estimators are reported by Bechtold and Paterson (2005) and Westfall et al. (2022). In summary, the NFI uses an area frame and a rotating panel design where the eastern United States is sampled using five or seven panels and the western United States is sampled using 10 panels. The sampling intensity is approximately one sample plot per 2400 ha of land and water. Each panel is assumed to produce a random equal probability sample. Under the rotating panel design it takes 10 years, 14 years, and 20 years to obtain a full set of remeasurements for the 5, 7, and 10 panel designs, respectively. Remeasured data are the basis for change estimates that include land use change and harvest removals.

All ownerships (public and private) and land uses (forest and non-forest) are sampled. Sample plots are permanent (locations do not change over time) and have a fixed area. Sample locations are mapped based on differing conditions in terms of land use, stand origin, forest type, and other forest characteristics. When the sample locations are remeasured, changes in the areal extent of conditions are recorded. Each plot may therefore exhibit a mixture of land use transitions on these conditions. Because of these sampling protocols, it is a straightforward process to construct an area change matrix for each sample plot in the population. Plot-level area change matrices form the bases for our conversion estimator and, for our analysis, three different area change matrices are used (Fig. 2). A forest-non forest matrix (Fig. 2A) is used to estimate net forest change. A natural forest-planted forest—non forest matrix (Fig. 2B) is used to estimate conversion of natural forest to planted forest and net change in natural forest. A forest—agriculture—other non-forest matrix (Fig. 2C) is used to es-

Fig. 2. Plot-level area change matrices used in this analysis. Panel A is the forest—non-forest matrix, panel B is the natural forest—planted forest—non-forest matrix, and panel C is the forest—agriculture—non-forest matrix. Note that in panel C the non-forest land use does not include agriculture.

A

		Time 2: Forest	Time 2: Non-forest
Time 1	Forest	*F-F*	*F-N*
	Non-forest	*N-F*	*N-N*

B

		Time 2: Natural forest	Time 2: Planted forest	Time 2: Non-forest
Time 1	Natural forest	F_n-F_n	F_n-F_p	F_n-N
	Planted forest	F_p-F_n	F_p-F_p	F_p-N
	Non-forest	N-F_n	N-F_p	N-N

C

		Time 2: Forest	Time 2: Agriculture	Time 2: Non-forest
Time 1	Forest	*F-F*	*F-A*	*F-N**
	Agriculture	*A-F*	*A-A*	*A-N**
	Non-forest	*N*-F*	*N*-A*	*N*-N**

Transitions

F-F = persistent forest	F_p-N = planted forest conversion to non-forest
F-N = forest conversion to non forest	N-F_n = non-forest conversion to natural forest
N-F = non-forest conversion to forest	N-F_p = non-forest conversion to planted forest
N-N = persistent non-forest	*F-A* = forest conversion to agriculture
F_n-F_n = persistent natural forest	*A-F* = agriculture conversion to forest
F_n-F_p = natural forest conversion to planted forest	*A-A* = persistent agriculture
F_n-N = natural forest conversion to non-forest	*A-N* = agriculture conversion to other non-forest
F_p-F_n = planted forest conversion to natural forest	*N-A* = other non-forest conversion to agriculture
F_p-F_p = persistent planted forest	* agriculture treated separately and not included in non-forest

timate forest conversion to agriculture. Data to construct the plot-level area transition matrices for the most recent set of remeasurements (Table 2) in the United States were downloaded from https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart.

In our analysis we rely on the United States NFI land use definitions where a forest land use is defined as "Forest land has at least 10% canopy cover of trees of any size, or has had at least 10% canopy cover of trees in the past, based on the presence of stumps, snags, or other evidence, and that will be naturally or artificially regenerated. Additionally, the land is not subject to nonforest use(s) that prevent normal tree regeneration and succession, such as regular mowing, intensive grazing, or recreation activities" (USDA 2025). Planted forest is the subset of forest land where clear signs of artificial regeneration are present. Non-forest land is defined as "Land that does not support, or has never supported, forests, and lands formerly forested where tree regeneration is precluded by development for other uses. Includes areas used for crops, improved pasture, residential areas, city parks, improved roads of any width and adjoining rights-of-way, power line clearings of any width, and noncensus water" (USDA 2025). Agriculture is a subset of non-forest land including both cropland and pasterland. The minimum area for any land use is 0.4 ha and the land use must be at least 36.6 m wide.

Estimator

Figure 2 demonstrates how the land use change and stand origin area change observations from each remeasured plot i can be organized into a k x k area change matrix, $\mathbf{A_i}$. The total sample area measured in each change category (elements of the matrices presenting in Fig. 2), for the population over the remeasurement period, is

$$(1)\qquad \underset{(k\,\times\,k)}{\mathbf{A}} = \sum_{i=1}^{n} \underset{(k\,\times\,k)}{\mathbf{A_i}}$$

where n is the total number of sample plots in the population. The estimated state transition probabilities of $\mathbf{A}$ over the remeasurement period are

$$(2)\qquad \underset{(k\,\times\,k)}{\widehat{\mathbf{P}}} = \underset{(k\,\times\,k)}{\mathbf{A}} \oslash \left(\underset{(k\,\times\,k)}{\mathbf{A}} \; \underset{(k\,\times\,k)}{\mathbf{1}} \right)$$

where $\mathbf{1}$ is a matrix of ones and $\oslash$ denotes Hadamard (element by element) division. The off-diagonal elements of $\widehat{\mathbf{P}}$ are estimated gross conversion rates (either gross loss or gross gain) and the diagonal elements are persistence rates (e.g., the amount of forest that remains forest over the remeasurement period). Total measured area in each state at time 1 and time 2 is $\underset{(k\,\times\,1)}{\boldsymbol{a}_1} = \underset{(k\,\times\,k)}{\mathbf{A}} \; \underset{(k\,\times\,1)}{\mathbf{1}}$ and $\underset{(k\,\times\,1)}{\boldsymbol{a}_2} = \underset{(k\,\times\,k)}{\mathbf{A}^{\mathrm{T}}} \; \underset{(k\,\times\,1)}{\mathbf{1}}$, respectively, where $\mathbf{1}$ is a vector of ones. The net percent change in states over the remeasurement period can be estimated by:

$$(3)\qquad \underset{(k\,\times\,1)}{\widehat{\boldsymbol{d}}} = 100 \left(\underset{(k\,\times\,1)}{\boldsymbol{a}_2} - \underset{(k\,\times\,1)}{\boldsymbol{a}_1} \right) \oslash \underset{(k\,\times\,1)}{\boldsymbol{a}_1}$$

Each element of $\widehat{\mathbf{P}}$ and $\widehat{\boldsymbol{d}}$ are ratio estimates and the ratio to size variance estimator presented by Westfall et al. (2022) can be easily implemented. However, in most situations either annual conversion estimates or 10-year net percent change estimates are of interest. $\widehat{\mathbf{P}}$ is annualized by $\widehat{\mathbf{P}}^{\frac{1}{\bar{r}}}$ which is solved by:

$$(4)\qquad \underset{(k\,\times\,k)}{\widehat{\mathbf{P}_{\mathrm{ann}}}} = e^{\frac{1}{\bar{r}}\log\left(\underset{(k\,\times\,k)}{\widehat{\mathbf{P}}}\right)}$$

where $\widehat{\mathbf{P}_{\mathrm{ann}}}$ is a matrix of annual state transition probabilities and $\bar{r}$ is an area weighted average of the remeasurement period (Van Deusen and Roesch 2009). The matrix logarithm is solved via power series provided $\left|\left|\widehat{\mathbf{P}} - \mathbf{I}\right|\right| \leq 1$, where $\mathbf{I}$ is an identity matrix. $\widehat{\mathbf{P}_{\mathrm{ann}}}$ is assumed to be fixed and it represents the average annualized conversion rates from remeasured data collected at intervals of $\bar{r}$ over a 2 $\bar{r}$ period. The 10-year transition probabilities, $\widehat{\mathbf{P}_{10}}$, can be calculated either by replacing $1/\bar{r}$ in eq. 4 with $10/\bar{r}$ or by calculating $\widehat{\mathbf{P}_{\mathrm{ann}}}^{10}$. Let $\boldsymbol{a}_1$ equal year 1 ($\boldsymbol{y}_1$) then $\widehat{\mathbf{P}_{10}}$ can be used to estimate the year 10 area of each state:

$$(5)\qquad \widehat{\boldsymbol{y}_{10}} = \boldsymbol{y}_1 \widehat{\mathbf{P}_{10}}$$

Equation 3 is then used to estimate net percent change by replacing $\boldsymbol{a}_1$ and $\boldsymbol{a}_2$ with $\boldsymbol{y}_1$ and $\widehat{\boldsymbol{y}_{10}}$, respectively.

We use bootstrap percentile confidence intervals (Efron and Tibshirani 1994) to estimate the precision of gross and net conversion rates estimates. For a population of interest, $B = 5000$ bootstrap replicates are created by randomly selecting n observations, with replacement, for each $b = 1$ to B replicates. For each b, the estimate of interest is constructed using the methodology previously introduced. This leads to a distribution of B estimates for the population of interest with the mean of those estimates being the bootstrap estimate. Bootstrap 95% confidence intervals are created by sorting the B estimates and selecting the 125$^{\mathrm{th}}$ estimate as the lower end of the confidence interval and the 4875$^{\mathrm{th}}$ estimate as the upper end of the 95% confidence interval (i.e., two-sided with 2.5% in each tail). The probability that the population estimate exceeds a critical value (e.g., 10-year net forest change < −1%) is the number of replicates where the critical value has been exceeded divided by B.

Our approach can also be used to construct short-term forecasts of net percent change in future years. For example, suppose $\boldsymbol{a}_2$ corresponds to 2020 and $\boldsymbol{y}_{2020}$ can be set to $\boldsymbol{a}_2$. A short-term projection to 2030 is then $\widehat{\mathbf{y}_{2030}} = \mathbf{y}_{2020}\widehat{\mathbf{P}_{10}}$ and eq. 3 can be used to calculate net percent change over this future period. However, it is more useful to construct scenarios to understand how changes in forest to non-forest conversions impact net forest change estimates. For example, does a population exceed the net forest loss threshold of 1% with 95% certainty when conversions of forest to non-forest increase by, say, 5% or 10%? Or, how much would forest to non-forest conversions need to increase for a population to exceed 1% net forest loss with 95% certainty? These questions can be answered by modifying the bootstrapping process previously described.

Typically, a bootstrap sample is drawn from an original sample of size n with an equal probability of $u_i = 1/n$. The bootstrap sample selection can be biased by adding a small

Table 3. Time periods for average annual conversion rate estimates, 10-year net change estimates, and 10-year net change projections for each Bureau of Economic Analysis (BEA) region.

BEA region	Median year of measurement	Median year of remeasurement	Time period for average annual conversion rate estimates	Time period for 10-year net change estimates	Time period for 10-year net change projections
Far West	2006	2016	2006–2016	2006–2016	2016–2026
Great Lakes	2012	2018	2012–2018	2012–2022	2022–2032
Mideast	2011	2018	2011–2018	2011–2018	2018–2028
New England	2013	2019	2013–2019	2013–2023	2023–2033
Plains	2013	2018	2013–2018	2013–2023	2023–2033
Rocky Mountain	2006	2016	2006–2016	2006–2016	2016–2026
Southeast	2013	2019	2013–2019	2013–2023	2023–2033
Southwest	2007	2017	2007–2017	2007–2017	2017–2027

quantity, v, to the selection probabilities for those elements one wants to preferentially bias towards selecting. For our application, we want to simulate an increase in the amount of forest to non-forest conversions. For those sample NFI plots where conversion from forest to non-forest was observed, a value of $v = 0.05$, for example denoting a 5% increase, is added resulting in:

$$u_i = \begin{cases} \dfrac{1+v}{n} & \text{plots with forest to nonforest transitions} \\ \dfrac{1}{n} & \text{plots without forest to nonforest transitions} \end{cases} \tag{6}$$

The probabilities are then scaled to 1 by $\pi_i = \frac{u_i}{\sum_{i=1}^{n} u_i}$. Each biased bootstrap sample of size n is drawn with probability π_i. Estimates of the bootstrap mean and confidence intervals are calculated as previously described.

Application

Our focus is on the measures described in various forest certification or regulatory standards (e.g., SFI, FSC, EUDR) and we estimate annual net natural forest change, 10-year net forest change, annual natural forest conversion to planted forest, and annual forest conversion to agriculture. The SFI fiber sourcing standard has set a critical value for net decadal forest change of −1% (i.e., net forest loss > 1%), therefore, we use this value. We use the critical value of 0.5% for net natural forest loss as described by the FSC standard. For annual forest conversion to agriculture and natural forest conversion to planted forest, we construct the estimate and its 95% confidence interval. Short-term projections of 10-year net forest change are also developed where we determine the % increase in forest to non-forest conversions that would cause each BEA region to exceed 1% 10-year net forest loss with 95% certainty. All analysis was performed using R (R Core Team 2021).

We examine these certification metrics and regulatory standards for the conterminous United States (excluding the state of Wyoming, which is just beginning to collect remeasurement data). Because sourcing regions for wood receiving facilities are confidential (Coulston et al. 2018), we use BEA regions of the United States for our analysis (Fig. 1). The United States NFI uses a rotating panel design which means that a range of measurement years and remeasurement years are included (Table 2). For our analysis we define the time period for average annual conversion rate estimates as the period between the median of the measurement year (time 1) and the median of the remeasurement year (time 2, Table 3). The time period for 10-year net forest change estimates is defined as time 1 and time 1 + 10. The time period for ten-year net forest change projections is defined as time 1 + 10 and time 1 + 20 (Table 3).

In some economic regions, there is a mix of panel designs (e.g., Southwest has a five-panel design in the eastern part of the region and a 10-panel design in the rest of the region). In these cases, within region, we grouped areas with like panel designs (pd) and calculate $\mathbf{A}_{\text{pd}}$, $\widehat{\mathbf{P}_{\text{pd}}}$, and $\widehat{\mathbf{P}_{\text{pd}_{\text{ann}}}}$ as described in eqs. 1, 2, and 4 respectively. We then combine across pd, within region, to estimate:

$$\underset{(k\,\times\,k)}{\widehat{\mathbf{A}_{\text{ann}}}} = \sum_{pd\,\in\,\{5,\,7,10\}} \left(\left(\underset{(k\,\times\,k)}{\mathbf{A}_{\text{pd}}} \; \underset{(k\,\times\,k)}{1} \right) \otimes \underset{(k\,\times\,k)}{\widehat{\mathbf{P}_{\text{pd}_{\text{ann}}}}} \right) \tag{7}$$

Equation 2 is then used to estimate $\widehat{\mathbf{P}_{\text{ann}}}$ by replacing $\mathbf{A}$ with $\widehat{\mathbf{A}_{\text{ann}}}$. Other components of the analysis are unchanged.

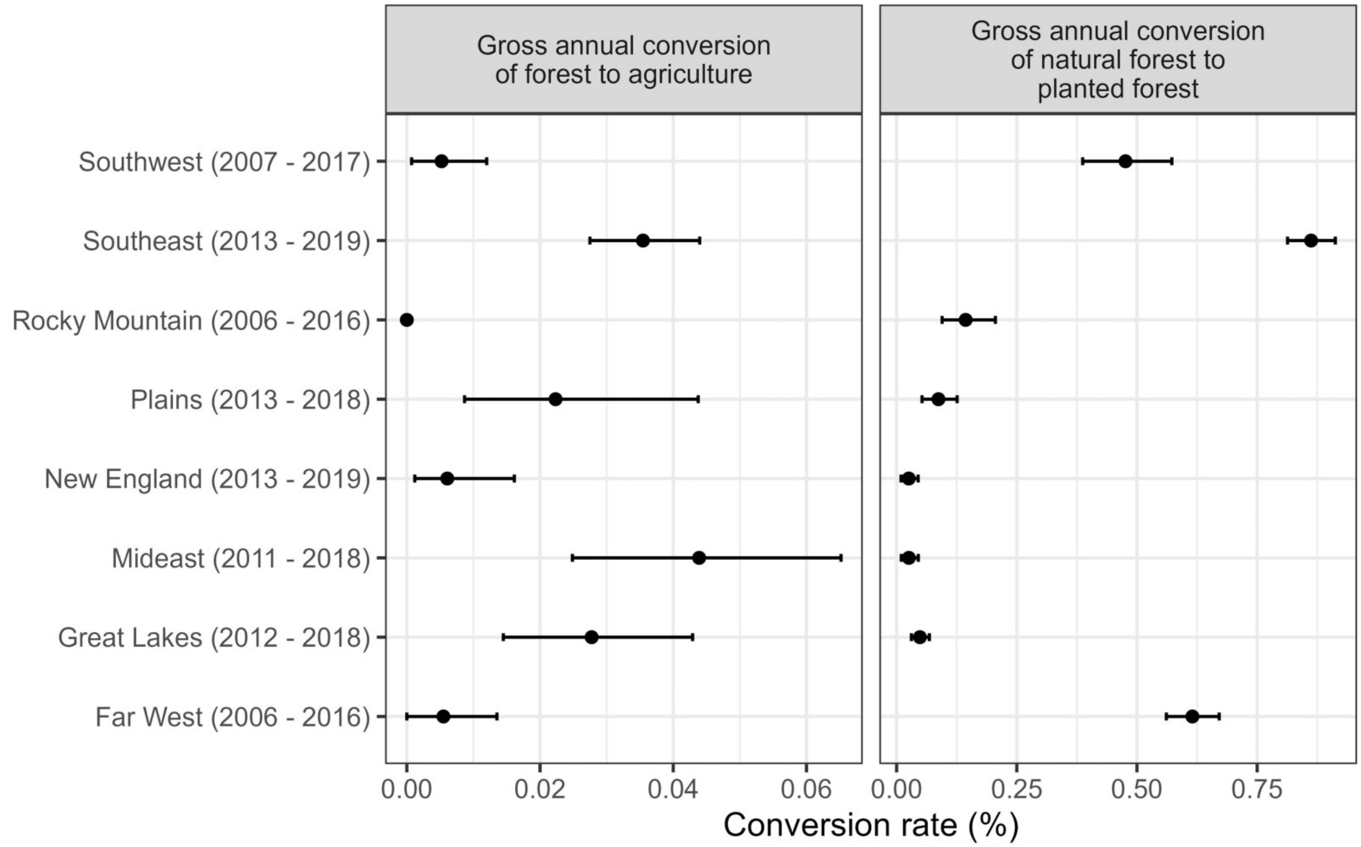
Results

Gross annual conversions

Gross average annual conversions of forest to agriculture were rare in all BEA region (Fig. 3). The largest average annual gross conversion rate was in the Mideast region (0.044%). No forest to agriculture conversions were observed in the Rocky Mountain region. In the Southeast region, where removals were largest, the gross average annual conversion of forest to agriculture was 0.035% with a 95% confidence interval of 0.027%–0.044%. In the Far West region, the 95% confidence interval for gross annual conversion to agriculture ranged from approximately 0% to 0.014%.

Gross average annual conversion of natural forest to planted forest was more common than gross annual conversion from forest to agriculture (Fig. 3). In general, larger annual conversion rates were estimated for areas with larger softwood removals such as the Southeast (0.86% annual conversion rate) and Far West (0.62% annual conversion rate) re-

Fig. 3. Estimates and 95% confidence intervals for gross average annual conversion of forest to agriculture, and gross annual conversion of natural forest to planted forest.



gions. The exception was the Southwest region (0.48% annual conversion rate) where most of the gross annual conversions from natural forest to planted forest occurred in the eastern part of the Southwest region.

Annual percent net natural forest change

Average annual net change in natural forest ranged from −0.4% in the Far West region to +0.05% in the Rocky Mountain region (Fig. 4). For all regions, except the Far West, the probability that average annual net change in natural forest was $\leq -0.5\%$ was $p = 0$. In the Far West region, the probability was $p = 0.01$. The average annual net natural forest change 95% confidence intervals for the Great Lakes, Plains, and Southwest regions included zero. However, the 95% confidence interval for the Southwest region was the widest of any region highlighting relatively large variability.

10-year percent net forest change

Estimates for 10-year percent net forest area change ranged from −1.58% in the Southwest region to +1% in the Rocky Mountain region (Fig. 4). Increasing forest area (i.e., net change > 0%) was only observed for the Rocky Mountain region. However, the probability that any region exceeded the 1% net forest loss threshold did not exceed $p = 0.95$. The Southwest region had the largest probability of exceeding the threshold ($p = 0.92$). The Southeast region and the Far West region (the two regions with the largest amount of roundwood removals) both had −1% net forest change (i.e., 1% net forest loss) and their respective probabilities for exceeding the loss threshold were $p = 0.52$ and $p = 0.51$.

Regions that are close to exceeding 1% in 10-year net forest loss with $p \geq 0.95$ may exceed the 1% loss threshold at $p = 0.95$ in a future period with relatively small increases in forest to non-forest conversion (Table 4). For example, in the Southwest region, a 4.9% increase in forest to non-forest conversions led to the region exceeding the 1% net forest loss threshold at $p = 0.95$ over the 2017–2027 projection period (Table 4). Similarly an 8.8% increase in forest to non-forest conversions resulted in the Southeast region exceeding 1% net forest loss over the 2023–2033 projection period. Conversely, the Rocky Mountain region had a net forest gain in the current period and our results suggest that it would require a 375.7% increase in forest to non-forest conversion for the region to exceed 1% net forest loss over the projection period.

Discussion

Our results suggest that both net and gross land conversions are rare in areas where roundwood is generally sourced for forest products. This does not imply that certain finer-scale areas do not have larger conversion rates but rather, across broad economic regions of the United States, land use choices and shifts in forest management are relatively small

Fig. 4. Estimates and 95% confidence intervals for annual net natural forest change and 10-year net forest change. The dotted vertical line indicates a net change of zero. The solid line represents the critical value as specified in the certification standard (−1% for 10-year net change and 0.5% for annual net natural forest change).

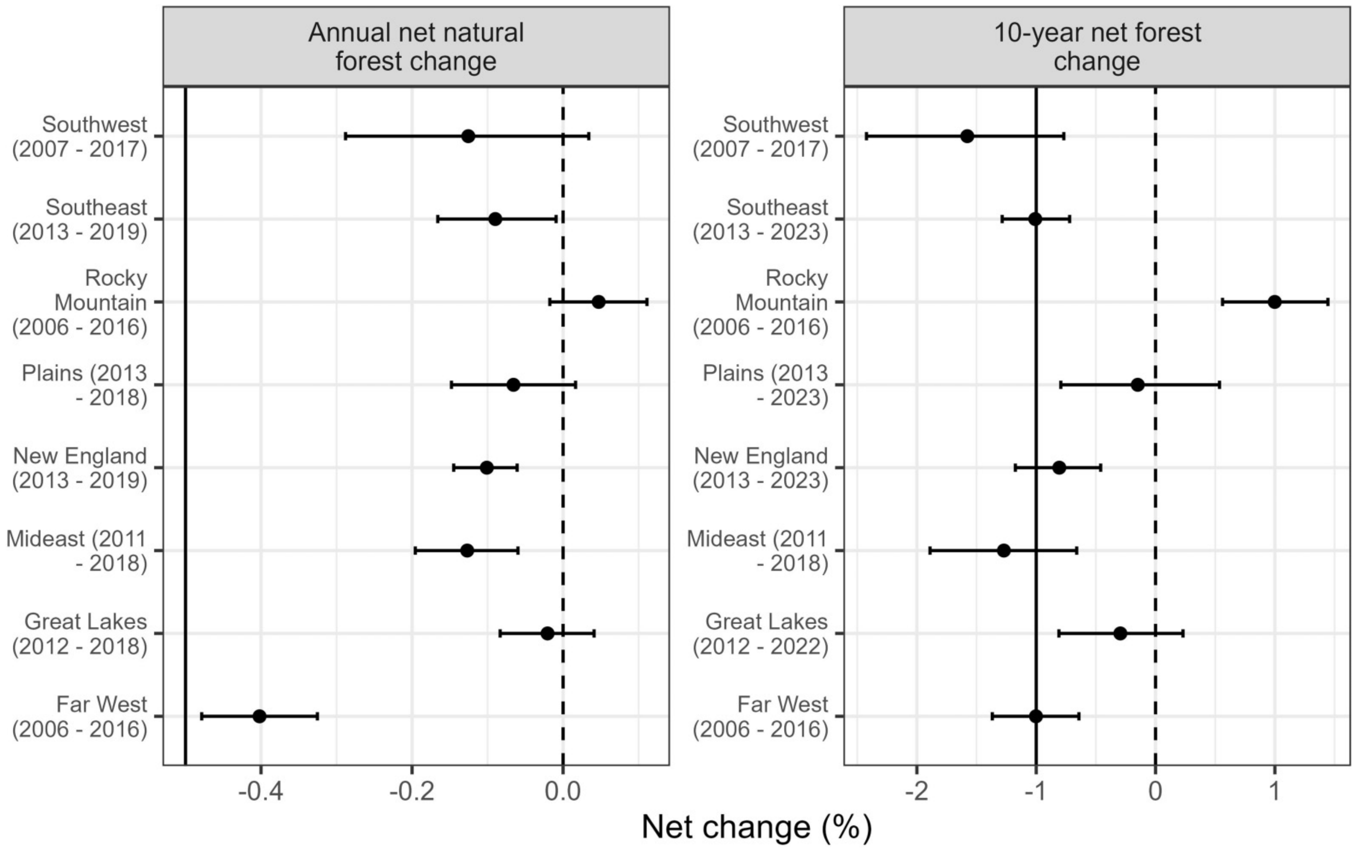


Table 4. Short term projections of 10-year net forest change estimates for each Bureau of Economic Analysis (BEA) region subject increased forest to non-forest conversion such that net forest loss exceeds 1% at $p = 0.95$.

BEA region	Current period estimate 10-year net forest change	Projection period	Increase forest to non-forest conversion	Projected 10-year net forest change	Lower 95% bootstrap interval	Upper 95% bootstrap interval
	(%)		(%)	(%)	(%)	(%)
Far West	−1.00	2016–2026	14.1	−1.31	−1.68	−0.95
Great Lakes	−0.29	2022–2032	52.9	−1.47	−2.03	−0.91
Mideast	−1.27	2018–2028	10.3	−1.52	−2.15	−0.90
New England	−0.81	2023–2033	39.1	−1.33	−1.73	−0.94
Plains	−0.15	2023–2033	64.9	−1.61	−2.34	−0.88
Rocky Mountain	1.00	2016–2026	375.7	−1.47	−2.03	−0.90
Southeast	−1.01	2023–2033	8.8	−1.25	−1.53	−0.96
Southwest	−1.58	2017–2027	4.9	−1.70	−2.52	−0.89

Note: See Table 3 for the years corresponding to the current period for each BEA region.

based on remeasured data. Conversion to urban and suburban land uses has been the largest driver of forest conversion in the United States (Wear 2011, Mihiar et al. 2023). However, the way in which population shifts influence developed land use patterns has changed over the last 20-years and land use dynamics have dampened from peaks in the 1980–2000 period (Bigelow et al. 2022). The 10-year net forest loss metric used by SFI seems to acknowledge that in the United States the choice of land use is made by the owner(s) of individual parcels and there is significant variability among individual landowner choices in terms of conversion regardless of whether it is conversion out of forest (gross loss) or into forest (gross gain). Therefore, defining conversion metrics and standards based on a longer timeframe that accounts for both gross loss and gross gain (gain − loss = net change) accounts for land use choices that increase carbon uptake (e.g., afforestation) as well as land use choices that increase carbon emissions.

There are few studies available to compare our results to but Renwick et al. (2025) and Homer et al. (2020) are two studies where comparisons can be made. Renwick et al. (2025) examined forest conversion to agriculture in the United States and found the average annual conversion rate was less than 0.04%. We found that, with the exception of the Mideast BEA region, average annual conversion was also less than 0.04%. Homer et al. (2020) found that average annual net forest loss was 0.21% for the conterminous United States which suggests a 10-year net loss of 2.1%. Our results suggest that all BEA regions had a smaller 10-year net forest loss rate than suggested by Homer et al. (2020). This discrepancy is likely because of forest use versus forest cover definitions where under a forest cover definition forest harvest and other forest disturbance that removes significant tree cover can be identified as a land cover change even though the land use remains forest (Coulston et al. 2014). To our knowledge, no recent studies are available to compare estimates of gross annual conversion of natural forest to planted forest or estimates of annual net change in natural forest to our results.

Typically, when gross loss statistics are presented, they are accompanied by net change statistics so there is a more complete picture of how land uses are transitioning over time (see, for example, Lark et al. 2020). Relative to other regions, the Southeast region showed large annual conversion rates from forest to agriculture and from natural forest to planted forest. However, the gross losses of natural forest to planted forest are more than offset by the gains in natural forest from planted forest resulting in a net decrease of planted forest in the region. The current remeasured data for the Southeast region suggests the area of planted forests has decreased on average 0.17% per year. Net annual decreases in planted forest were also observed in the Southwest (0.48%), Mideast (0.22%), and Great Lakes (0.17%) regions. Likewise, gross gains in forest from agricultural land outpaced gross loss to agriculture in roundwood producing areas of the Plains, Great Lakes, and Far West regions.

Given that planted forests only occupy a moderately small portion (17.8%) of the forest landbase used in this analysis, one would expect the net annual change in natural forest metric to be very similar to the 10-year net change in forest metric. However, based on the bootstrap replicates, correlation between these two metrics was moderate ($r = 0.58$) yet if we remove the Far West region when calculating the correlation coefficient there is a stronger relationship ($r = 0.95$). Anecdotally, the disturbances in the western United States led to an increase tree planting in the western United States (Dobrowski et al. 2024) and unlike the Southeast region, the Far West region has experienced an increase in planted forests. This suggests that increased planting due to restoration of burned (or other disturbances) areas somewhat drives forest planting and conversion out of natural forest in the western United States. It seems logical to avoid conflating forest planting for restoration, or other reasons, with forest planting for timber production in conversion metrics.

Alternative gross and net change estimators for United States NFI data are offered by Van Deusen and Roesch (2009; Weighted Maximum Likelihood Estimator) and Van Deusen and Roesch (2009; Temporally Indifferent Estimator). Our approach can be described as an extension of Van Deusen and Roesch (2009) where they arranged the NFI information into a binomial indicator variable to estimate the probability of a state change between forest and non-forest states. Our approach extends this idea by estimating the probability of changes among states, the probability of remaining in a single state over time, and accounts for the fact that the area of the population is fixed (i.e., the amount of land and water is fixed and hence changes to one element in the transition matrix influences other elements in the matrix). Our approach also allows for short-term projections to inform forest management and fiber sourcing planning efforts. However, all three approaches (Weighted Maximum Likelihood, Temporally Indifferent, and our approach) are valid for use with the United States NFI.

The methods presented in this paper offer a simple projection model to examine likely 10-year net forest change rates if there are increases in conversions of forest to non-forest (gross loss). However, gross forest gains (non-forest conversion to forest) are equally as important. For example, net forest loss can increase by increased forest conversion to non-forest, decreased conversion of non-forest to forest, or both. Our approach can be easily modified to project 10-year net forest change rates under decreases in non-forest conversion to forest. This would be accomplished using eq. 6 but rather that adding a small value to the inclusion probabilities of those observations one wants to bias the selection towards, a small value would be subtracted from the inclusion probabilities of the observations one wants to bias against.

Our use of broad economic regions was necessary because the sourcing area used by any single roundwood receiving mill is unknown. When roundwood receiving mills do report receipt information to, for example, the United States NFI Resource Use program, the data are confidential (Coulston et al. 2018; Westfall et al. 2022). However, we have developed an estimation approach that can be used by forest products companies to understand forest conversion in their local supply regions and further understand how future shifts in conversion rates may impact sustainability criterion for those sourcing areas, even small sourcing regions (e.g., 0.5 million ha). For example, a mill could define its supply region by a draw radius (e.g., 40 km) and select the set of inventory plots that fall within the draw radius from the mill. The set of selected plots would then form the basis of a local analysis of forest conversion metrics using the approaches provided here.

Our approaches rely on public United States NFI data, an open-source statistical program (R Core Team 2021), and are easily portable to web-based application through R Shiny, for example. There are some limitations to our approach. Because we rely on the United States NFI data, estimates should be constructed for fiber supply regions with a large enough sample size to provide the desired precision. We recommend regions of at least 0.5 million ha which offers a sample size of approximately 160 inventory plots. Though, in some cases, this may be insufficient, depending on the variability of the sample. However, the precision of conversion estimates may be increased using small area estimation techniques such as those offered by Rao and Molina (2015), many of which are available as supplemental packages to R. A small area estimation framework also facilitates the use of relevant remote sensing data in a way that estimates, and their precision, are available (Coulston et al. 2021).

Conclusion

Quantifying forest conversion metrics is increasingly important to the forest products sector both from a certification and regulatory perspective. While EUDR implementation has been delayed, the current EUDR regulations offer just one example of potential future regulations. Regardless, sound approaches are needed to estimate conversion rates across scales ranging from local fiber supply areas to regions. Here we present a new estimation approach that not only allows for estimating conversion metrics of interest but also for constructing short-term projections under user defined scenarios. Further, this approach relies on publicly available data and software which facilitates use by a broad set of both domestic and international users.

We have three primary conclusions from the analysis of conversion metrics for roundwood producing economic regions in the United States. First, forest conversions to agriculture are not currently an issue in roundwood producing regions of the United States. Second, natural forest conversions to planted forest are offset in half of the economic regions by landowners choosing to use natural regeneration methods over replanting and further, planting to reforest disturbed areas (or other reasons) may be conflated with natural forest conversion. Third, there are several economic regions where 10-year net forest loss is close to exceeding 1% net loss at $p = 0.95$. These areas include the southwest, southeast, and far west economic regions. Local fiber supply area analyses, in these economic regions, will likely be important for producing certified products.

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Data availability

The data used in this analysis are publically available at the following web address: https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart. The analysis code is available up request from the corresponding author.

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Competing interests

The authors declare there are no competing interests.

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