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Applying Ratio-of-Means Estimation for Annualized Components of Volume Change in Forest Resource Monitoring

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Abstract

Forest inventory estimates of annualized net growth, removals, and mortality provide a standardized metric for a wide range of management and policy assessments. Commonly, plot-level annualized values are determined by dividing the periodic change by the length of the time interval. Subsequent estimation of means constitutes a mean-of-ratios (MOR) estimation approach. However, due to potential bias concerns for the MOR estimator, the ratio-of-means (ROM) estimator is generally preferred by forestry practitioners. National forest inventory data from six states in the United States were used to compare MOR and ROM annualized change estimation. Generally, MOR and ROM performed similarly when there was little variation among plot measurement intervals. Differences between MOR and ROM increased as variability among measurement intervals increased, with the largest observed differences being in the 3%–4% range. The ROM estimator also resulted in more precise estimates than MOR, although in many cases the differences were trivial. ROM estimation can be negatively affected if the mean of the measurement intervals assigned to unvisited nonforest plots is incongruent with the mean for forested field–visited plots. Nonetheless, if this complication is not present or can be ameliorated, the ROM estimator appears to perform better than MOR across various populations.

Study Implications: Forest inventory volume change results are usually reported on a per-year basis to make them more interpretable by data users. This study compared the use of the typical mean-of-ratios (MOR) approach with an alternative ratio-of-means (ROM) concept. In a simulation study that examined six different populations of forest inventory plots, the ROM method generally had smaller bias and uncertainty statistics than the MOR approach. Thus, the ROM estimation offers forest inventory practitioners a more robust method for calculating annualized change statistics. The use of accurate estimations to inform management and policy decisions is critical to effective stewardship of forest resources.

Keywords: growth, harvest, mortality, bias, mean-of-ratios, remeasurement interval

Sustainable management of forest resources requires information pertaining to both current status and amounts of change. The latter is particularly important from a temporal perspective, as change information characterizes progress towards various goals such as preferred species composition, ensuring removals do not exceed growth, and other forest management aspirations (Pukkala 2016). In many cases, forest managers rely on forest inventory data for quantitative assessments of status and trends in forest conditions (Kangas 2010; Smith and Gray 2021). Typically, forest inventory data are obtained periodically or on a continual basis. Periodic inventories consist of an initial measurement of all sample plots, followed by remeasurement at a later point in time with no information being obtained during the interval (Köhl and Scott 2000). Although status and trend information are available from periodic inventories, any changes in forest condition are unknown during the years between measurement cycles (Gillespie 2000). The desire for a consistent update of current status and trend information has led to increasing preference for annual (panelized) forest inventories, where a subset of the sample plots is measured every year (Gschwantner et al. 2016) and population estimates are annually updated (Bechtold and Patterson 2005). Subsequently, plots are remeasured at a time interval approximately equal to the cycle length. Although the design has remeasurement of each plot occurring at the specified interval, operational factors around staffing, budgets, and travel cause plots to be measured sooner or later than intended.

Regardless of inventory implementation, remeasured plot data serve a multitude of purposes, including monitoring of mortality events (Edgar et al. 2019; Shaw, Steed, and DeBlander 2005), productivity (Charru et al. 2010), carbon flux (Herold et al. 2011), land use conversion (Van Deusen and Roesch 2009), and various other issues related to changes in forest resources (Tinkham et al. 2018). In many cases, estimates of periodic change are converted to an annualized mean that standardizes the values for ease of interpretation and consistent usage among data users (Hoover and

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Smith 2021). Often, this is accomplished by calculating the plot-level change and dividing by the time interval between plot measurements (Poso 2006; Scott et al. 2005; Talbot et al. 2014) and estimating annual population change using those values. An alternative approach would be to divide the overall observation of change over the time interval by the average time interval between successive inventories as determined from individual plot remeasurement intervals. The former method equates to using a mean-of-ratios (MOR) estimator, which has been shown to produce nontrivial bias in estimates from forest inventory data (Ek 1971; Salas and Gregoire 2010). The latter approach resembles implementation of a ratio-of-means (ROM) estimator that is often used in forest inventory estimation to report results on a per-unit area basis, for example, volume per hectare of forest (Zarnoch and Bechtold 2000). However, use of the ROM estimator for annualized change estimates appears to be infrequent, with the average time interval being defined as a constant (Lanz et al. 2019; Smith et al. 2007). In this study, use of the ROM estimator in the context of estimating annualized change in growth, removals, and mortality volume is investigated where the remeasurement interval is considered a random variable (Roesch 2008). Performance of the ROM estimator is evaluated in comparison to the typically used MOR estimator for a poststratified sampling design.

Methods

Data

Evaluation of estimator performance was conducted using United States national forest inventory data collected by the Forest Inventory and Analysis (FIA) program (https://www.fia.fs.usda.gov). FIA implements a panelized inventory in which a spatially-balanced portion of the plots are measured each year, with all plots being measured over a period of 5–10 years depending on the state. The same process is repeated temporally such that each plot gets remeasured every 5–10 years. For efficiency, plots are only field-visited for measurement if forest land area occurs within the plot as determined from evaluation of high-resolution remotely-sensed information or if there were forest measurements taken at the previous measurement. Unvisited "office" plots have observations of zero for forest attributes by definition. The sampling design is quasi-systematic with a sampling intensity of approximately 1 plot per 5,937 ac (2,428 ha) (Reams et al. 2005). The field data are collected on plots composed of four circular subplots with a 24 ft (7.32 m) radius, with one subplot located at plot center and the remaining three subplots centered at azimuths 120°, 240°, and 360° and distance of 120 ft (36.58 m) from plot center. In California, 58.9 ft (17.95 m) radius macroplots colocated at subplot centers are also used (Bechtold and Scott 2005). In forested areas, trees having a diameter at breast height (DBH) ≥5.0 in. (12.70 cm) are measured on subplots; large trees with DBH ≥ 24.0 in. (60.96 cm) are measured on the macroplots in California. Tree merchantable volumes are determined from species and location-specific statistical models and are aggregated to a plot-level value for estimation purposes. Volume change for each plot is determined as the difference in volume as determined from plot measurements taken at two points in time. The remeasurement interval is recorded to the nearest 0.1 years. Data from remeasured plots in Ohio, Mississippi, Maine, Montana, Minnesota, and California were used as the populations to be sampled. For each state, the most recent plot measurement taken through inventory year 2018 was considered as the ending measurement and the plot observation taken during the previous cycle served as the initial measurement. A summary of relevant data attributes is provided in Table 1.

Within each state studied (Table 1) are G subpopulations called estimation units (EU), where G varies depending on the state. A poststratified sampling design is used within each EU, where the poststrata classifications and weights are determined from wall-to-wall remotely sensed information and the sample plots are assigned to poststrata based on the plot center location. Approaches to delineating the EU and establishing the poststrata vary among states.

Analysis

The analysis focused on annualized estimates of primary forest inventory change components—net growth, removals, and mortality in units of cubic volume (Burrill et al. 2023). Estimation was performed based on the FIA poststratified sampling design using the poststratified estimators described by Scott et al. (2005). The mean ($\bar{y}_{gh}$) and variance of the mean ($v\left(\bar{y}_{gh}\right)$) for each poststratum h in EU g are calculated from

$$\bar{y}_{gh} = \frac{\sum_{i}^{n_{gh}} y_{ghi}}{n_{gh}} \tag{1}$$

$$v\left(\bar{y}_{gh}\right) = \frac{\left(1 - \frac{n_{gh}}{N_{gh}}\right) \sum_{i}^{n_{gh}} \left(y_{ghi} - \bar{y}_{gh}\right)^2}{n_{gh}\left(n_{gh} - 1\right)} \tag{2}$$

where y_{ghi} is the observed value for plot i in poststratum h within EU g, n_{gh} is the number of sample plots in poststratum h within EU g, and N_{gh} is the number of population plots in poststratum h within EU g.

Estimates of the total and variance of the total for EU g are calculated by aggregating across the H poststrata. The poststratum means ($\bar{y}_{gh}$) and poststratum weights (W_{gh}) are used in equation (3) to determine the estimated EU mean ($\bar{y}_g$). The estimated variance of the EU mean ($v\left(\bar{y}_g\right)$) includes a second term to account for the variability due to random poststratum sample sizes (Scott et al. 2005) and $\sum_{h=1}^{H} n_{gh} = n_g$. Both the means and variances are adapted to the population total ($\hat{y}_g$) via simple expansion (Gregoire and Valentine 2008), in other words, multiplied by the population size (N_g):

$$\hat{y}_g = N_g \bar{y}_g = N_g \sum_{h=1}^{H} W_{gh} \bar{y}_{gh} \tag{3}$$

$$v\left(\hat{y}_g\right) = N_g^2 v\left(\bar{y}_g\right) = \frac{N_g^2}{n_g}\left[\sum_{h=1}^{H} W_{gh} n_{gh} v\left(\bar{y}_{gh}\right) + \sum_{h=1}^{H}\left(1 - W_{gh}\right)\frac{n_{gh}}{n_g} v\left(\bar{y}_{gh}\right)\right] \tag{4}$$

When a mean-of-ratios (MOR) approach is taken, the estimation proceeds as shown above using the annualized plot change value, that is, plot-level change in component volume divided by the plot remeasurement period are the y_{ghi} to obtain $MOR_g = \hat{y}_g$ and $v(MOR_g) = v\left(\hat{y}_g\right)$ via (1)–(4).

However, additional calculations are required in a ratio-of-means (ROM) estimation context. In this case, estimates for the numerator are obtained using the plot-level volume

Table 1. Summary statistics for mean net growth, removals, and mortality volume and plot measurement interval by state. N = number of plots in the state, G = number of estimation units in the state, and S = total number of strata across all estimation units.

State	Attribute	Minimum	Mean	Maximum	SD
Ohio	Net growth (m^3/ha)	-26.7	0.8	39.1	2.9
N = 3960	Removals (m^3/ha)	0.0	0.6	72.7	4.0
G = 15	Mortality (m^3/ha)	0.0	0.6	29.5	2.0
S = 40	Remeasurement (years)	4.0	5.6	7.8	0.6
Mississippi	Net growth (m^3/ha)	-55.6	4.7	43.9	6.1
N = 5166	Removals (m^3/ha)	0.0	1.8	91.5	6.1
G = 6	Mortality (m^3/ha)	0.0	0.8	39.8	2.1
S = 21	Remeasurement (years)	2.9	7.2	10.3	1.3
Maine	Net growth (m^3/ha)	-22.8	2.6	20.9	2.8
N = 3444	Removals (m^3/ha)	0.0	2.0	73.4	6.5
G = 26	Mortality (m^3/ha)	0.0	0.9	26.3	1.7
S = 60	Remeasurement (years)	4.1	5.0	6.1	0.3
Montana	Net growth (m^3/ha)	-45.5	-0.2	15.9	3.0
N = 8918	Removals (m^3/ha)	0.0	0.1	34.8	1.2
G = 56	Mortality (m^3/ha)	0.0	0.8	49.2	3.2
S = 190	Remeasurement (years)	4.0	10.0	13.1	0.3
Minnesota	Net growth (m^3/ha)	-36.9	0.6	60.1	2.2
N = 17312*	Removals (m^3/ha)	0.0	0.3	68.3	2.6
G = 15	Mortality (m^3/ha)	0.0	0.4	39.7	1.6
S = 48	Remeasurement (years)	4.0	5.0	6.4	0.2
California	Net growth (m^3/ha)	-77.7	0.5	35.9	4.0
N = 12726	Removals (m^3/ha)	0.0	0.2	70.1	2.4
G = 3	Mortality (m^3/ha)	0.0	0.7	83.6	3.4
S = 308	Remeasurement (years)	3.9	9.9	12.5	0.3

change as the y_{ghi}. The denominator calculations proceed identically, notationally substituting x_{ghi} for y_{ghi} to differentiate between numerator (plot volume change) and denominator (plot measurement interval) attributes (i.e., plot measurement interval is indicated by x_{ghi}), in pursuit of the annualized EU total and its variance:

$$ROM_g = N_g \frac{\hat{y}_g}{\hat{x}_g} = N_g \frac{N_g \bar{y}_g}{N_g \bar{x}_g} \tag{5}$$

$$v\left(ROM_g\right) = \frac{N_g^2}{x_G^2}\left[v\left(\bar{y}_g\right) + ROM_g^2 v\left(\bar{x}_g\right) - 2ROM_g cov\left(\bar{y}_g, \bar{x}_g\right)\right] \tag{6}$$

The covariance of the means is calculated from

$$cov\left(\bar{y}_g, \bar{x}_g\right) = \frac{1}{n_g}\left[\sum_{h=1}^{H} W_{gh} n_{gh} cov\left(\bar{y}_{gh}, \bar{x}_{gh}\right) + \sum_{h=1}^{H}\left(1 - W_{gh}\right)\frac{n_{gh}}{n_g} cov\left(\bar{y}_{gh}, \bar{x}_{gh}\right)\right] \tag{7}$$

$$cov\left(\bar{y}_{gh}, \bar{x}_{gh}\right) = \frac{\left(1 - \frac{n_{gh}}{N_{gh}}\right)\sum_i^{n_{gh}}\left(y_{ghi} - \bar{y}_{gh}\right)\left(x_{ghi} - \bar{x}_{gh}\right)}{n_{gh}\left(n_{gh} - 1\right)} \tag{8}$$

As the preceding formulae are applied to calculate EU totals and associated variances, state-level estimates are determined as the sum of EU values, that is, $MOR = \sum_{g=1}^{G} MOR_g$ and $v\left(MOR\right) = \sum_{g=1}^{G} v(MOR_g)$, with analogs to obtain ROM and $v\left(ROM\right)$, respectively.

Monte Carlo simulations were conducted by drawing a random sample from the "population" of plots (Table 1) in each EU for $m = 1$ to M iterations ($M = 25{,}000$). ROM and MOR estimates for each state were generated from each selected sample using the formulae above for annualized total net growth, removals, and mortality volume. Generally, about 10% of the plots were randomly selected into the sample at each iteration, with some deviations to ensure a minimum poststratum sample size ($n_h \geq 2$). For each change component, the Monte Carlo simulation results for MOR estimates were summarized by the mean of the estimates $\overline{MOR}$, mean of the variances (from (4) $\bar{v}\left(MOR\right)$, and variance of the estimates $v_{MC}\left(MOR\right)$:

$$\overline{MOR} = \frac{\sum_{m=1}^{M} MOR}{M} \tag{9}$$

$$\bar{v}\left(MOR\right) = \frac{\sum_{m=1}^{M} v\left(MOR\right)}{M} \tag{10}$$

$$v_{MC}\left(MOR\right) = \frac{\sum_{m=1}^{M}\left(MOR - \overline{MOR}\right)^2}{M\left(M-1\right)} \tag{11}$$

ROM estimates were summarized in a likewise fashion. For the purpose of evaluating estimator bias, the true annualized population change values (R_{POP}) were determined for each state and component using all N plots (Table 1). The total volume change for a state was calculated from entire population of observations:

$$\hat{Y} = \sum_{g=1}^{G}\sum_{h=1}^{H}\sum_{i=1}^{N_h} y_{ghi} \quad (12)$$

Analogously, x_{ghi} were used to obtain the population total measurement interval $\hat{X}$. Subsequently, the overall annualized population total results from

$$R_{POP} = \frac{\hat{Y}}{\hat{X}} \quad (13)$$

The percent bias in the MOR and ROM estimators were calculated from

$$B_{MOR} = \frac{\left(\overline{MOR} - R_{POP}\right)}{R_{POP}} \times 100 \quad (14)$$

$$B_{ROM} = \frac{\left(\overline{ROM} - R_{POP}\right)}{R_{POP}} \times 100 \quad (15)$$

Similarly, performance of the variance estimators was assessed via percentage of difference comparisons between $\bar{v}\,(MOR)$ and $\bar{v}\,(ROM)$ and the Monte Carlo results $v_{MC}\,(MOR)$ and $v_{MC}\,(ROM)$, respectively given as

$$D(\bar{v}_{MOR}) = \left[\bar{v}\,(MOR) - v_{MC}\,(MOR)\right]/v_{MC}\,(MOR) \times 100 \quad (16)$$

$$D(\bar{v}_{ROM}) = \left[\bar{v}\,(ROM) - v_{MC}\,(ROM)\right]/v_{MC}\,(ROM) \times 100 \quad (17)$$

Finally, comparisons between MOR and ROM estimators were made to ascertain which estimator provided a smaller percent sampling error based on a root mean squared error ($RMSE$) criterion:

$$RMSE_{MOR} = \sqrt{B_{MOR}^2 + \bar{v}\,(MOR)} \quad (18)$$

$$SE\%_{MOR} = \frac{RMSE_{MOR}}{\overline{MOR}} \times 100 \quad (19)$$

$$RMSE_{ROM} = \sqrt{B_{ROM}^2 + \bar{v}\,(ROM)} \quad (20)$$

$$SE\%_{ROM} = \frac{RMSE_{ROM}}{\overline{ROM}} \times 100 \quad (21)$$

Results

A range of outcomes were observed across the six states and components of change. The ROM estimator was essentially unbiased for all states and change components, with B_{ROM} ranging from –0.22% to 0.10% (Table 2). Similarly, the MOR estimator exhibited little bias for all change component estimates in Montana, net growth and mortality in Maine, and mortality in California. However, biases that may be considered nontrivial were indicated by B_{MOR} values of 0.76% (mortality in Ohio) to 3.91% (net growth in Mississippi). Generally, there was consistency in B_{MOR} magnitude among the change components within a state; for example, Montana had the smallest B_{MOR} and Mississippi had the largest B_{MOR} for all change components.

Variance estimators corresponding with $\bar{v}\,(MOR)$ (4) and $\bar{v}\,(ROM)$ (6) performed nearly identically as assessed by (10) when compared to the simulation variances from (11) of $v_{MC}\,(MOR)$ and $v_{MC}\,(ROM)$, respectively. In all cases, the formula-based variance estimates exceeded those resulting from the sampling simulations from roughly 3% to 37% (Table 3). Further, the differences were nearly identical between

Table 2. State-level percentage of bias in ROM and MOR estimates by change component using poststratified estimation.

	B_{ROM}			B_{MOR}		
State	**Net growth**	**Removals**	**Mortality**	**Net growth**	**Removals**	**Mortality**
California	0.00%	0.10%	-0.06%	0.89%	1.04%	-0.38%
Ohio	0.07%	-0.22%	0.07%	1.57%	2.09%	0.76%
Mississippi	0.04%	-0.04%	0.09%	3.91%	3.52%	2.84%
Minnesota	-0.03%	0.06%	-0.03%	1.59%	2.32%	1.20%
Maine	0.02%	-0.01%	0.05%	0.18%	1.45%	0.07%
Montana	0.02%	0.12%	0.01%	0.17%	0.21%	0.15%

Table 3. State-level growth component percent differences between mean formula-based variances and the corresponding variance of the estimates from Monte Carlo simulations for ROM and MOR estimations.

	$D(\bar{v}_{ROM})$			$D(\bar{v}_{MOR})$		
State	**Net growth**	**Removals**	**Mortality**	**Net growth**	**Removals**	**Mortality**
California	33.3%	13.8%	37.4%	33.4%	13.8%	37.7%
Ohio	13.3%	10.8%	13.8%	13.3%	10.6%	13.8%
Mississippi	2.7%	2.8%	2.8%	2.7%	2.6%	3.1%
Minnesota	5.7%	7.6%	6.8%	5.6%	7.2%	6.5%
Maine	8.1%	6.9%	6.9%	8.2%	6.6%	6.8%
Montana	25.0%	26.0%	26.1%	25.2%	25.7%	26.3%

ROM and MOR for each component of change within a state. Subsequent investigation revealed these outcomes were likely due to small sample sizes within some strata. Large-sample simulations conducted using the entire state as a single EU and no poststratification (i.e., simple random sample) produced results where $\bar{v}(MOR) \cong v_{MC}(MOR)$ and $\bar{v}(ROM) \cong v_{MC}(ROM)$.

Despite the lack of conformity between formula-based and Monte Carlo variances, it is still of interest to evaluate the relative error associated with ROM and MOR estimators. As assessed by percentage of sampling error (SE%), the ROM estimator provides more precision than the MOR estimator in most cases (Table 4). However, the differences are generally of little practical importance, with perhaps the exception of Mississippi where, for example, the ROM SE% is nearly 24% smaller than the MOR SE% for net growth.

Discussion

Although the consistent performance of the ROM estimator in terms of small bias was apparent, the difference between ROM and MOR estimates varied among the states. For example, in Montana, the performance of the estimators was quite similar, whereas the starkest differences occurred in Mississippi (Table 2). These differences appear to be at least in part attributable to the distributions of the measurement intervals. As noted by Zarnoch and Bechtold (2000), MOR and ROM are equivalent when the denominator is a constant. Thus, near-equivalence may be inferred when measurement intervals are almost constant. Examination of the differences in measurement interval distributions between Montana and Mississippi reveals a nearly constant measurement interval for Montana in contrast to considerable variation occurring in Mississippi (figure 1). The distribution of measurement intervals in Ohio may be considered intermediate compared with Montana and Mississippi, and this seems to corroborate that the magnitude of MOR bias is at least partly related to the variability found in the interval distribution (figure 1, Table 2).

In general, MOR tended to have a positive bias (Table 2), which translates into MOR estimates of change being too large. It appears this is the result of "outliers" being produced from the division of change by measurement interval at the plot level in MOR implementation. These outliers appear to occur more prevalently with plots having relatively short measurement intervals, which is not offset by similar behavior in plots having longer measurement intervals. In particular, division by relatively small numbers tends to produce large ratio outcomes that in some cases have the effect of shifting the mean towards a larger value than would be obtained in the ROM approach, where more stability arises due to the use of mean values in the ratio calculation.

Table 3 shows that the variance formulae for MOR and ROM estimations tend to be similarly conservative compared with the simulation variance of the estimates. Using the FIA inventory plots as the population resulted in small sample sizes for small strata, which in some samples resulted in large variance estimates. Thus, the distributions of variance estimates tended to be right skewed, which increased the values of $\bar{v}(MOR)$ and $\bar{v}(ROM)$ relative to the more symmetric distribution of MOR and ROM estimates that served as the basis for $v_{MC}(MOR)$ and $v_{MC}(ROM)$. Consequently, it is important to create poststrata of sufficient size such that adequate sample sizes are attained therein. An illustrative example is given by California, where many relatively small poststrata exist (308 poststrata across 3 EU, Table 1), which corresponds with the largest $D(\bar{v}_{MOR})$ and $D(\bar{v}_{ROM})$ found in this study. Westfall et al. (2011) generally suggest a minimum of ten sample plots per poststratum, although Cochran (1977) and Särndal et al. (1992) suggest thirty and twenty plots, respectively, as adequate for valid large-sample approximations. Nonetheless, it was shown that ROM is generally comparable or superior to MOR in a percentage of error context (Table 4), which suggests no disadvantage is incurred when the ROM estimator is used instead of the commonly used MOR approach for annualized change.

On a related note, the typical implementation of assigning a consistent measurement date for office plots will often create a point mass at the specified cycle length (e.g., 5 years) for this subset of plots. However, field plots will typically have a distribution of measurement intervals that ideally have a mean value near the specified cycle length (figure 1, Table 5). Thus, the variability in measurement intervals arises almost exclusively from field-visited plots. Further, inclusion of the office-plot point mass results in a smaller estimated variance than would be obtained if all plots were designated for a field visit. It might be considered whether this practice provides a satisfactory expression of the error due to sampling, or would it be more appropriate that the office plot measurements have an interval distribution that either mimics that of field plots or are based on, for example, image dates used for office plot interpretations. A cursory examination of this question suggests variance increases are trivial (<1%) when using an office plot interval distribution that was modified to be similar to that of field plots. Presumably, these differences would be small in cases where the original interval distributions

Table 4. Percentage of sampling error (SE%) based on (19) by state and change component for ROM and MOR estimates. Italics indicate the smaller SE% between ROM and MOR.

	ROM			MOR		
State	Net growth	Removals	Mortality	Net growth	Removals	Mortality
California	11.36%	*17.35%*	*8.85%*	*11.30%*	17.58%	8.86%
Ohio	*15.66%*	*30.20%*	*14.72%*	15.70%	31.01%	14.77%
Mississippi	*4.73%*	*13.62%*	*11.07%*	6.21%	14.89%	11.96%
Minnesota	*8.49%*	*19.14%*	*7.91%*	8.66%	19.33%	7.96%
Maine	*5.23%*	*17.16%*	*9.70%*	5.24%	17.39%	9.75%
Montana	*49.63%*	38.29%	*12.49%*	49.83%	*38.25%*	12.55%

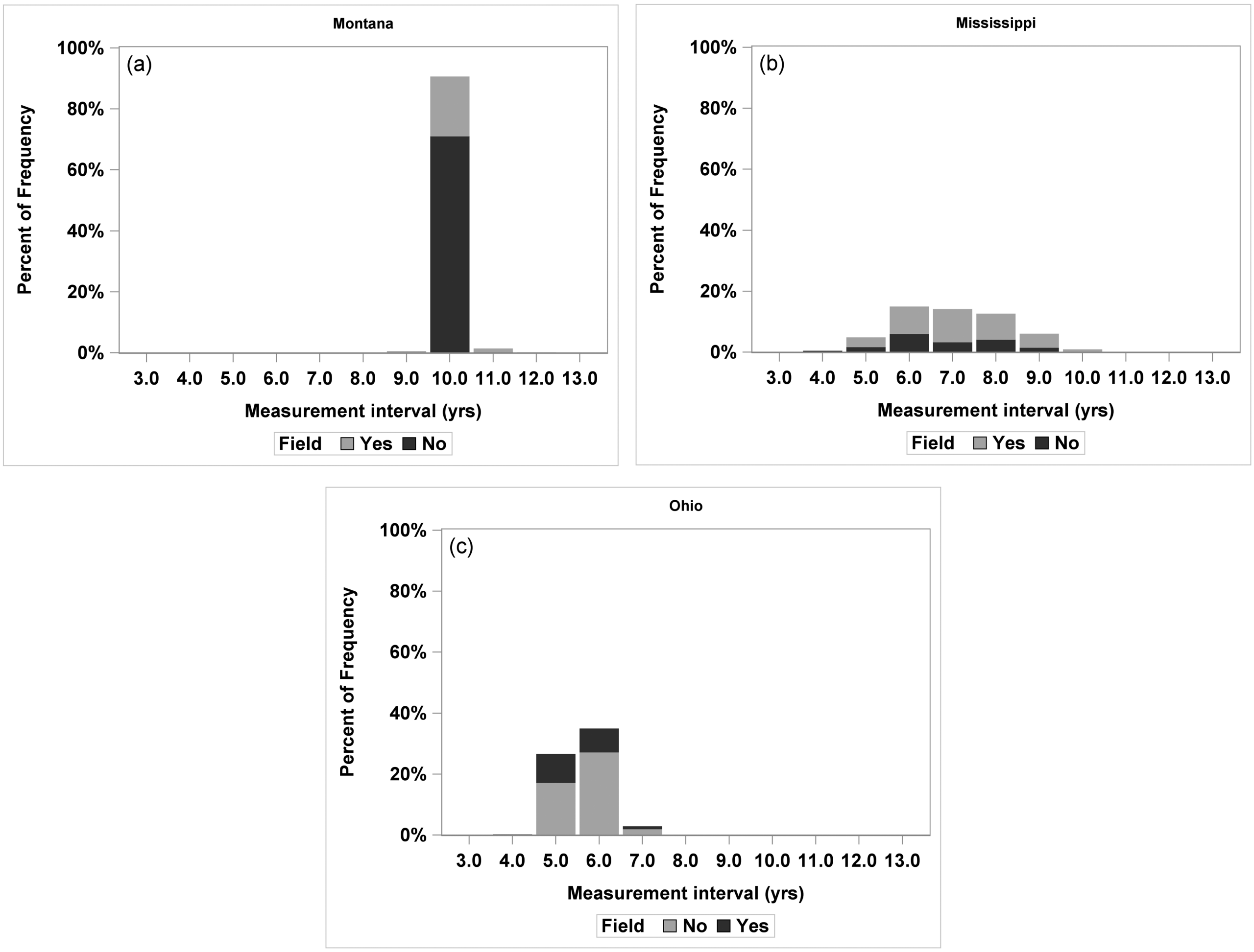

Figure 1 Measurement interval distributions for field and office plots in the states of (a) Montana, (b) Mississippi, and (c) Ohio

Table 5. Mean and standard deviation (in parentheses) of plot measurement intervals (years) and the bias percent imparted in the ROM denominator due to differences between all plots and field plots.

State	All	Field	Office	Bias (%)
Ohio	5.60 (0.55)	5.60 (0.64	5.59 (0.49	-0.14%
Mississippi	7.20 (1.25)	7.20 (1.22)	7.18 (1.44)	-0.04%
Maine	5.03 (0.30)	5.03 (0.31)	5.01 (0.08)	-0.05%
Montana	10.01 (0.27)	10.03 (0.48)	10.00 (0.05)	-0.15%
Minnesota	5.02 (0.24)	4.92 (0.32)	5.08 (0.16)	2.09%
California	9.92 (0.30)	9.91 (0.45)	9.92 (0.17)	0.02%

were somewhat similar or when the number of office plots is relatively small. The extent to which estimator variances are affected by unequal variability between interval distributions of field and office plots may be an issue for further contemplation and possibly more focused investigation, including area estimates of nonforest land use change based on office plot observations.

The results shown reflect the characteristics of the populations being sampled as developed directly from the FIA database. However, there is an additional issue to confront in regard to obtaining reliable estimates of change components when using the ROM estimator. Specifically, the mean remeasurement interval depends on both office and field plots. Field plot measurement intervals are based on actual plot measurement dates; however, office plots do not have a specific measurement date as the plot "observations" are collected as needed each year from an existing remotely sensed information source. Regardless of the measurement interval for office plots, their contribution to the numerator mean will always be change observations of zero, but the chosen measurement interval may affect the denominator mean of ROM and could potentially produce an inaccurate result if the mean interval is different between office and field plots. Thus, it is of considerable importance to ensure compatibility between office and field remeasurement intervals. Evaluations of this phenomenon for the states used in this study show good agreement, with the exception of Minnesota, where a seemingly trivial difference translates into the ROM denominator estimate being about 2% too large with consequent underestimation of annualized change (Table 5).

Further investigation of this phenomenon revealed that part of the issue was due to a change in office measurement date protocols. The automated office plot measurement date was assigned as January 15 of the plot measurement year through 2009; however, in 2010 and subsequent years, it was changed to be June 1 of the measurement year. Thus, office plot measurement intervals shifted from 5.0 years to 5.4 years, even though the intended cycle length was still 5 years. Under the typical MOR estimation approach, this change was considered trivial as there was no effect on the estimates. For ROM estimation, the effect was mitigated to some extent in this analysis due to only 2009 and later plots being used for change evaluation, along with a small increase in the average measurement interval of field plots that occurred simultaneously. The largest effect would have occurred in 2014, when all office plots would exhibit the protocol change influence. In this case, the denominator bias would increase from 2.09% to 3.74%.

A secondary issue with measurement intervals assigned to office plots also deserves mention. Under FIA protocols, all plots that had a forest condition at the previous measurement are assigned for a field visit even if the current assessment via remotely sensed information indicates only nonforest conditions exist. This is done to verify in situ the loss of forest area as well as to reconcile the status of each tree recorded previously (e.g., removal due to land use change). Generally, the only measurement intervals completely affected by the office date assignment are those that were entirely nonforest at the previous and current measurement. However, other situations can occur, such as forest conditions arising on previously nonforest areas. In this case, the date of the initial measurement would be that of the invariant office plot protocol (e.g., June 1), whereas the subsequent measurement would be based on the actual field visit date. Thus, the measurement interval may not accurately represent the period over which forest change occurred and potentially skew the denominator mean in ROM estimation. Replacing the invariant office protocol with interpreted image dates could more precisely represent office measurement dates and resulting remeasurement periods for both office-to-field forest changes and for potential application to office plot–based land use area changes as mentioned above. Other considerations in this context include changes in cycle lengths or delays in field work plot completion that may disrupt measurement interval patterns.

Finally, it should be acknowledged that concern has been expressed regarding combining observations that arise from differing time lengths to estimate annual change. For example, Roesch (2007) illustrates that different measurement interval bases represent different population parameters. Roesch and Van Deusen (2012) note that observed values of change on sample plots depend on the length of the measurement interval. This may only be of minor concern for relatively short measurement intervals but may become nontrivial as measurement interval lengths increase or the distribution of measurement intervals widens. It was also pointed out that temporal indifference is implicitly assumed in most national forest inventory (NFI) programs when estimating annualized change, which invokes an assumption that the mean annual change over a period of years and the change for any single year are equal. Subsequently, research on various forest inventory change estimators and their performance appear in Roesch and Van Deusen (2013), Roesch (2014), and Roesch (2019). Yet, adoption of these methods appears to be absent in NFI estimations, presumably due to lack of awareness or implementation complexity considerations. As such, the typical approach of dividing plot change by plot measurement interval (MOR in this study) seems to be quite dogmatic in forest change assessments (Holdaway et al. 2017; Lewis et al. 2009; McNellis et al. 2021). Alternatively, implementation of the ROM annualized change estimator should be relatively straightforward, as similarly constructed ROM estimators are already used and incorporate explicit covariance calculations; for example, current status of cubic volume per unit-area of forestland (Scott et al. 2005).

Conclusion

In many NFI that use permanent sample plots, the distributions of individual plot measurement intervals can vary substantially due to various factors related to operational implementation. Except in cases where the intervals are (nearly) constant, the MOR estimation method can produce inaccurate annualized change estimates of growth, removals, and mortality volume (and by extension, presumably tree biomass and carbon change as well). In contrast, the ROM approach seems robust across a range of measurement interval scenarios and also generally provides a smaller percentage of sampling error. However, implementation of ROM requires congruence in measurement interval means between office and field plots such that the overall mean is representative of the forested subset on which volume change actually occurs. This aspect may require special attention when modifications are considered in the interval assignment protocols for office plots or when intentional or unintentional changes occur during the inventory cycle that cause shifts in expected measurement interval distributions.

Although the magnitude of differences in estimates between MOR and ROM ranged from negligible in some states to 2%–4% in other states, some concern about the differences may be warranted in the context of practical and statistical interpretation of results. For example, a larger annualized change estimate from MOR compared with ROM could exceed the threshold of expert opinion norms and elicit a potentially needless concern that unexpected trends are occurring. Similarly, differences in both estimates and sampling errors between MOR and ROM could result in one method indicating a statistically significant change has occurred, whereas the alternative suggests the change estimate is not statistically different from zero. On a related note, the study results also reiterated the importance of adequate poststratum sample sizes to ensure accurate estimates of variance that are critical to obtaining valid conclusions from statistical hypothesis tests. In forest inventories with fixed sample sizes, a compromise between the number of poststrata and poststratum sample sizes may be needed to balance the precision gains of poststratification with the necessity of fulfilling minimum sample size requirements.

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Conflict of Interest

None declared.

Data Availability

The data are publicly available from the FIA database (https://apps.fs.usda.gov/fia/datamart/datamart.html).

Literature Cited

Bechtold, W.A., and P.L. Patterson. 2005. *The Enhanced Forest Inventory and Analysis Program—National Sampling Design and Estimation Procedures*, 85. USDA Forest Service General Technical Report SRS-80, Asheville, NC: Southern Research Station.

Bechtold, W.A., and C.T. Scott. 2005. "The Forest Inventory and Analysis Plot Design." In *The Enhanced Forest Inventory and Analysis Program—National Sampling Design and Estimation Procedures*, edited by W.A. Bechtold and P.L. Patterson, 37–52. USDA Forest Service General Technical Report SRS-80. Asheville, NC: Southern Research Station.

Burrill, E.A., A.M. DiTommaso, J.A. Turner, S.A. Pugh, G. Christiansen, C.J. Perry, L.C. Lepine, D.M. Walker, M.A. Williams, and B.L. Conkling. 2023. *The Forest Inventory and Analysis Database: Database Description and User Guide Version 9.1 for Phase 2*. USDA Forest Service. https://usfs-public.app.box.com/v/FIA-FIADB-UserGuides/file/1465060362673.

Charru, M., I. Seynave, F. Morneau, and J.D. Bontemps. 2010. "Recent Changes in Forest Productivity: An Analysis of National Forest Inventory Data for Common Beech (*Fagus sylvatica* L.) in North-Eastern France." *Forest Ecology and Management* 260 (5): 864–874. https://doi.org/10.1016/j.foreco.2010.06.005.

Cochran, W.G. 1977. *Sampling Techniques*, 3rd ed, 428. New York: John Wiley & Sons.

Edgar, C.B., J.A. Westfall, P.A. Klockow, J.G. Vogel, and G.W. Moore. 2019. "Interpreting Effects of Multiple, Large-Scale Disturbances Using National Forest Inventory Data: A Case Study of Standing Dead Trees in East Texas, USA." *Forest Ecology and Management* 437 (8): 27–40. https://doi.org/10.1016/j.foreco.2019.01.027.

Ek, A.R. 1971. "A Comparison of Some Estimators in Forest Sampling." *Forest Science* 17 (1): 2–13.

Gillespie, A.J.R. 2000. "Pros and Cons of Continuous Forest Inventory: Customer Perspectives." In *Integrated Tools for Natural Resources Inventories in the 21st Century*, edited by M. Hansen and T. Burk, 60–66. USDA Forest Service General Technical Report NC-212. St. Paul, MN: North Central Forest Experiment Station.

Gregoire, T.G., and H.T. Valentine. 2008. *Sampling Strategies for Natural Resources and the Environment*, 1st ed, 474. Boca Raton, FL: Chapman and Hall/CRC.

Gschwantner, T., A. Lanz, C. Vidal, M. Bosela, L. Di Cosmo, J. Fridman, P. Gasparini, *et al*. 2016. "Comparison of Methods used in European National Forest Inventories for the Estimation of Volume Increment: Towards Harmonisation." *Annals of Forest Science* 73 (4): 807–821. https://doi.org/10.1007/s13595-016-0554-5.

Herold, M., R.M. Román-Cuesta, D. Mollicone, Y. Hirata, P. Van Laake, G.P. Asner, C. Souza, *et al*. 2011. "Options for Monitoring and Estimating Historical Carbon Emissions from Forest Degradation in the Context of REDD+." *Carbon Balance and Management* 6 (1): 1–7.

Holdaway, R.J., T.A. Easdale, F.E. Carswell, S.J. Richardson, D.A. Peltzer, N.W. Mason, A.M. Brandon, *et al*. 2017. "Nationally Representative Plot Network Reveals Contrasting Drivers of Net Biomass Change in Secondary and Old-Growth Forests." *Ecosystems* 20 (5): 944–959.

Hoover, C.M., and J.E. Smith. 2021. "Current Aboveground Live Tree Carbon Stocks and Annual Net Change in Forests of Conterminous United States." *Carbon Balance and Management* 16 (1): 1–12.

Kangas, A.S. 2010. "Value of Forest Information." *European Journal of Forest Research* 129: 863–874.

Köhl, M., and C.T. Scott. 2000. "A Comparison of Periodic Versus Permanent Surveys." In *Integrated Tools for Natural Resources Inventories in the 21st Century*, edited by M. Hansen and T. Burk, 94–103. USDA Forest Service General Technical Report NC-212. St. Paul, MN: North Central Forest Experiment Station.

Lanz, A., C. Fischer, and M. Abegg. 2019. "Sampling Design and Estimation Procedures." In *Swiss National Forest Inventory–Methods and Models of the Fourth Assessment*, edited by C. Fischer and B. Traub, 39–92. Berlin/Heidelberg: Springer.

Lewis, S., G. Lopez-Gonzalez, B. Sonké, *et al*. 2009. "Increasing Carbon Storage in Intact African Tropical Forests." *Nature* 457 (7232): 1003–1006.

McNellis, B.E., A.M. Smith, A.T. Hudak, and E.K. Strand. 2021. "Tree Mortality in Western US Forests Forecasted using Forest Inventory and Random Forest Classification." *Ecosphere* 12 (3): e03419.

Poso, S. 2006. "Change Monitoring with Permanent Sample Plots." In *Forest Inventory: Methodology and Applications*, edited by A. Kangas and M. Maltamo, 65–84. Dordrecht, The Netherlands: Springer Science & Business Media.

Pukkala, T. 2016. "Which Type of Forest Management Provides most Ecosystem Services?" *Forest Ecosystems* 3 (1): 1–16.

Reams, G.A., W.D. Smith, M.H. Hansen, W.A. Bechtold, F.A. Roesch, and G.G. Moisen. 2005. "The Forest Inventory and Analysis Sampling Frame." In *The Enhanced Forest Inventory and Analysis Program—National Sampling Design and Estimation Procedures*, edited by W.A. Bechtold and P.L. Patterson, 21–36. USDA Forest Service General Technical Report SRS-80. Asheville, NC: Southern Research Station.

Roesch, F.A. 2007. "The Components of Change for an Annual Forest Inventory Design." *Forest Science* 53 (3): 406–413. https://doi.org/10.1093/forestscience/53.3.406.

Roesch, F.A. 2008. "An Alternative View of Continuous Forest Inventories." *Forest Science* 54 (4): 455–464. https://doi.org/10.1093/forestscience/54.4.455.

Roesch, F.A. 2014. "Toward Robust Estimation of the Components of Forest Population Change." *Forest Science* 60 (6): 1029–1049. https://doi.org/10.5849/forsci.13-132.

Roesch, F.A. 2019. "Composite Estimators for Forest Growth Derived from Symmetric, Varying-Length Observation Intervals." *Forests* 10 (5): 409. https://doi.org/10.3390/f10050409.

Roesch, F.A., and P.C. Van Deusen. 2012. "Monitoring Forest/Non-Forest Land Use Conversion Rates with Annual Inventory Data." *Forestry* 85 (3): 391–398. https://doi.org/10.1093/forestry/cps037.

Roesch, F.A., and P.C. Van Deusen. 2013. "Time as a Dimension of the Sample Design in National-Scale Forest Inventories." *Forest Science* 59 (6): 610–622. https://doi.org/10.5849/forsci.12-075.

Salas, C., and T.G. Gregoire. 2010. "Statistical Analysis of Ratio Estimators and their Estimators of Variances When the Auxiliary Variate is Measured with Error." *European Journal of Forest Research* 129 (5): 847–861.

Särndal, C.E., B. Swensson, and J. Wretman. 1992. *Model Assisted Survey Sampling*. New York: Springer Science & Business Media.

Scott, C.T., W.A. Bechtold, G.A. Reams, W.D. Smith, J.A. Westfall, M.H. Hansen, and G.G. Moisen. 2005. "Sample-Based Estimators used by the Forest Inventory and Analysis National Information Management System." In *The Enhanced Forest Inventory and Analysis Program–National Sampling Design and Estimation Procedures*, edited by W.A. Bechtold and P.L. Patterson, 53–77. USDA Forest Service General Technical Report SRS-80. Asheville, NC: Southern Research Station.

Shaw, J.D., B.E. Steed, and L.T. DeBlander. 2005. “Forest Inventory and Analysis (FIA) annual inventory answers the question: What is happening to pinyon-juniper woodlands?” *Journal of Forestry* 103 (6): 280–285.

Smith, J.E., L.S. Heath, and M.C. Nichols. 2007. *US Forest Carbon Calculation Tool: Forest-Land Carbon Stocks and Net Annual Stock Change*, 34. USDA Forest Service General Technical Report NRS-13. Newtown Square, PA: Northern Research Station.

Smith, R.J., and A.N. Gray. 2021. “Strategic Monitoring Informs Wilderness Management and Socioecological Benefits.” *Conservation Science and Practice* 3 (9): e482.

Talbot, J., S.L. Lewis, G. Lopez-Gonzalez, R.J. Brienen, A. Monteagudo, T.R. Baker, T.R. Feldpausch, *et al*. 2014. “Methods to Estimate Aboveground Wood Productivity from Long-Term Forest Inventory Plots.” *Forest Ecology and Management* 320 (2014): 30–38.

Tinkham, W.T., P.R. Mahoney, A.T. Hudak, G.M. Domke, M.J. Falkowski, C.W. Woodall, and A.M. Smith. 2018. “Applications of the United States Forest Inventory and Analysis Dataset: A Review and Future Directions.” *Canadian Journal of Forest Research* 48 (11): 1251–1268. https://doi.org/10.1139/cjfr-2018-0196.

Van Deusen, P.C., and F.A. Roesch. 2009. “Estimating Forest Conversion Rates with Annual Forest Inventory Data.” *Canadian Journal of Forest Research* 39 (10): 1993–1996. https://doi.org/10.1139/x09-075.

Westfall, J.A., P.L. Patterson, and J.W. Coulston. 2011. “Post-Stratified Estimation: Within-Strata and Total Sample Size Recommendations.” *Canadian Journal of Forest Research* 41 (5): 1130–1139. https://doi.org/10.1139/x11-031.

Zarnoch, S.J., and W.A. Bechtold. 2000. “Estimating Mapped-Plot Forest Attributes with Ratios of Means.” *Canadian Journal of Forest Research* 30 (5): 688–697. https://doi.org/10.1139/x99-247.