For. Sci. 61(1):17–24
http://dx.doi.org/10.5849/forsci.13-202

biometrics

Selection of Forest Inventory Cycle Length Based on Growth Rate and Measurement Variability

James A. Westfall

As pressures on forest resources mount, there is an increasing need for up-to-date information on which sound management and policy decisions can be made. This is evident in the adoption of shorter inventory cycle lengths for national forest inventories in the past few decades. While these intensified efforts are meritorious, substantial efficiency can be lost if cycle lengths are too short in relation to growth in the population. Specifically, if growth is small in relation to measurement variation, the signal-to-noise ratio is small and considerable expense is incurred to obtain data of limited usefulness. To address this issue, the relationships between measurement variation and growth rates were examined across a spatial gradient in the eastern United States. As tree measurements are often not used directly, these relationships were also analyzed in the context of tree biomass prediction models of varying complexity. The results indicated that for latitude range N 30–38 degrees, where many fast-growing plantations are found, cycle lengths as short as 3 years may be acceptable if the biomass model only relies on tree diameter; however, increased cycle lengths should be chosen for more northerly latitudes. Longer cycle lengths are also suggested when employing more complex biomass models requiring additional inputs such as tree height and crown ratio, which are subject to higher levels of measurement variability. The methods provide a framework for determining cycle lengths that may considerably improve the efficiency and effectiveness of ongoing forest inventory and monitoring efforts.

Keywords: error propagation, signal-to-noise ratio, tree biomass, data quality

Many nations have implemented a national forest inventory (NFI) to assess and monitor forest resources (Söderberg 2000, Gillis et al. 2005, Tomppo 2006), and now in response to initiatives such as the United Nations program on Reducing Emissions from Deforestation and Forest Degradation (REDD) program, many other countries are currently developing NFI programs (Maniatis and Mollicone 2010). A key output of nearly all NFI efforts is sample-based estimates for attributes of interest (e.g., forestland area or net cubic volume). Apart from providing a current evaluation of relevant forest characteristics, another primary use of NFI data is to evaluate change over time. For example, it may be of interest to assess harvest sustainability between successive inventory cycles. Such inquiries provide valuable information to inform management and policy decisions that can have wide-ranging effects on forest resources.

Traditionally, NFIs were conducted on a periodic basis, e.g., data would be collected once every decade or so (Gillespie 1999, Brassel and Lischke 2001). More recently, the desire to have continually updated information has led to annualized designs where a portion of the sample plots are measured every year (Bechtold and Patterson 2005, Tomppo et al. 2010). In these annualized inventories, the cycle length is the number of years between successive measurements of the same cohort of sample plots. Generally, cycle lengths are approximately 5–10 years and are usually determined from funding availability and the need to capture effects of extreme events or burgeoning trends. However, it is not often considered that the ability to accurately measure forest attributes should also be a determining factor. Analyses of measurement repeatability for many forest inventory variables collected in the US NFI were presented by Pollard et al. (2006) and Westfall (2009). The results show that some measurements have very high repeatability while others are subject to considerable variation among observers. When trying to capture trends between successive measurements of forest inventory plots, high levels of measurement variability can make it difficult to capture statistically significant differences. As such, inventory cycle lengths should take into consideration the measurement variability of key variables as well as growth rates such that the magnitude of growth (or change) is of sufficient extent to overcome the measurement variation. This paper examined the relationships between measurement repeatability and tree growth rates to inform decisions on forest inventory cycle lengths. Specifically, the objectives were to (1) quantify the distribution of measurement variability for several key inventory variables by tree size class, (2) assess rates of growth in these variables across a spatial gradient, (3) examine the relationships between measurement variation and growth using tree biomass prediction models of varying complexity, and (4) using these relationships, establish a framework for selecting inventory cycle lengths.

Manuscript received December 17, 2013; accepted April 24, 2014; published online May 29, 2014.

Affiliations: *James A. Westfall (jameswestfall@fs.fed.us), USDA Forest Service, Northern Research Station, Newtown Square, PA.*

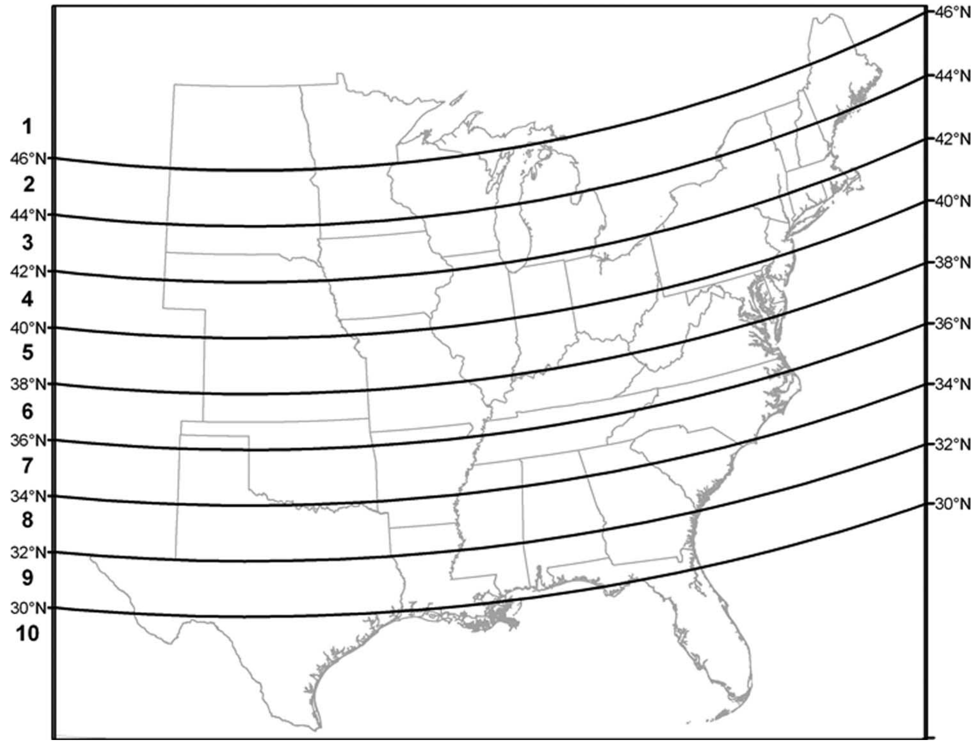

Figure 1. Map of study area and latitude bands.

Methods

Data

The data used in this study came from two sources within the Forest Inventory and Analysis (FIA) program of the USDA Forest Service. The first set of data was from a subset of production inventory plots that were selected to receive a quality assurance (QA) audit. In addition to the production crew measurements, a second set of measurements from the same trees taken a short time later (within 2 weeks) by the audit field crew was available. The audit crew had no knowledge of the results from the initial inventory measurement. There were 45,528 measured trees encompassing 3,712 sample plots of ~1/6 acre in size across 37 states in the southern and northern FIA regions (Figure 1). The plots were measured from 2006–2010. These data are referred to as the QA data hereafter.

The second set of data consisted of standard inventory measurements collected by FIA across the same geographic area (Figure 1). These data were collected during the period 2001–2010. A 5-year inventory cycle length was used and as such, the 2000 –2005 data represented an initial plot measurement (T1) and the 2006–2010 data represented a subsequent measurement of the same plots (T2). This allowed for a direct assessment of change over time. These change data consisted of 53,361 plots having measurements on over 1 million trees with a minimum dbh of 12.7 cm. The underlying sampling and plot designs are outlined by Bechtold and Patterson (2005) and the data collection protocols are given in USDA Forest Service (2007). This data set is referred to as the growth data hereafter.

Growth Rates

Remeasurement of the same plots at an interval of approximately 5 years provided field-based change observations for dbh (*D*), total height (*H*), and crown ratio (*CR*) while also allowing for change observations for total tree biomass (*B*) predicted from models using these variables at each point in time. For this study, the change over time in these variables across the entire region was not particularly useful as growth rates varied substantially within the region due to differences in temperature, day and growing season lengths, precipitation, and numerous other factors. As these factors generally exhibit systematic trends as latitude changes, the region was divided into 10 latitudinal bands (Figure 1). The first band included all land in the United States below N 30 degrees. Beginning at N 30 degrees and proceeding northward, the next eight bands had a width of 2 degrees, with the last band containing all area in the United States above N 46 degrees (Figure 1). The amount of data in each band varied with land base and amounts of forest contained therein. Changes in *D*, *H*, and *CR* from remeasured trees were calculated within each band by hardwood/softwood species group (Table 1). From these data, the primary interest was the mean change, hereby denoted as $\hat{\mu}_{Xik}$, where X indicates the variable of interest (e.g., *D, H, CR*), i signifies hardwood (H) or softwood (S) group, and k indicates the latitude band.

Measurement Variation

The QA data were used to assess the distributions of measurement differences as a means of quantifying observer-to-observer variability. Specifically, differences between two measurements (audit crew minus production crew) of the same trees were evaluated for *D, H*, and *CR*. It was also of interest to understand how these differences affected tree biomass prediction. To this end, nonlinear models were fitted to predict total tree biomass under three predictor variable scenarios representing the potential range of model complexity found across various forest inventory programs: (1) using *D* only, (2) using *D* and *H,* and (3) using *D, H*, and *CR*. The model formulations were

Table 1. Mean and standard deviation (in parenthesis) of growth over a 5-year interval for diameter at breast height (D), total height (H), and crown ratio (CR) by species group and latitude band.

Species group	Latitude degrees	No. of trees	Diameter (cm)	Height (m)	Crown ratio (%)
Hardwood	>46	97,358	1.20 (0.64)	0.55 (1.59)	−0.36 (7.67)
Hardwood	44–46	119,840	1.39 (0.66)	0.61 (1.61)	0.82 (7.68)
Hardwood	42–44	73,250	1.62 (0.73)	0.78 (1.62)	0.99 (7.66)
Hardwood	40–42	73,211	1.62 (0.75)	0.78 (1.63)	1.18 (7.63)
Hardwood	38–40	68,913	1.63 (0.78)	0.71 (1.63)	−1.47 (7.60)
Hardwood	36–38	113,461	1.58 (0.74)	0.76 (1.64)	−1.76 (7.52)
Hardwood	34–36	83,439	1.53 (0.74)	1.03 (1.65)	−0.69 (7.64)
Hardwood	32–34	49,332	1.63 (0.72)	1.05 (1.62)	−0.71 (7.94)
Hardwood	30–32	32,175	1.72 (0.71)	0.98 (1.58)	−2.54 (7.96)
Hardwood	<30	4,358	1.73 (0.73)	0.66 (1.54)	−1.58 (7.97)
Softwood	>46	72,015	1.15 (0.56)	0.66 (1.06)	−0.72 (7.90)
Softwood	44–46	84,186	1.31 (0.57)	0.74 (1.06)	−0.90 (7.57)
Softwood	42–44	25,586	1.37 (0.66)	0.96 (1.12)	−0.24 (7.30)
Softwood	40–42	8,215	1.42 (0.66)	0.91 (1.09)	−0.90 (7.72)
Softwood	38–40	8,317	1.44 (0.58)	1.07 (1.09)	−4.61 (7.20)
Softwood	36–38	26,073	2.11 (0.59)	1.75 (1.16)	−2.91 (6.78)
Softwood	34–36	38,515	2.77 (0.63)	2.38 (1.18)	−3.10 (6.62)
Softwood	32–34	45,143	3.23 (0.63)	2.81 (1.21)	−3.94 (6.61)
Softwood	30–32	37,605	3.17 (0.64)	2.83 (1.23)	−6.88 (6.39)
Softwood	<30	4,192	2.18 (0.62)	2.23 (1.20)	−3.78 (6.32)

Table 2. Mean and standard deviation (in parenthesis) of measurement differences for diameter at breast height (*D*), total height (*H*), crown ratio (*CR*), and predicted biomass from models 1–3.

Diameter (cm)	Hardwood	Softwood
12.7–22.6	−0.030 (0.53)	−0.028 (0.43)
22.7–32.7	−0.019 (0.67)	−0.028 (0.62)
32.8–42.9	−0.004 (0.65)	−0.069 (0.62)
43.0+	−0.057 (1.70)	−0.046 (1.74)
Total height (m)		
≤7.6	−0.316 (1.69)	−0.125 (0.80)
7.7–15.2	−0.087 (1.30)	−0.023 (0.95)
15.3–22.8	0.149 (1.61)	0.053 (1.20)
22.9+	0.376 (2.03)	0.123 (1.51)
Crown ratio (%)		
0–24	−3.731 (8.01)	−1.767 (5.72)
25–49	0.071 (7.12)	0.143 (6.32)
50–74	3.173 (9.73)	1.658 (9.74)
75+	4.519 (10.85)	3.236 (10.13)
Biomass (kg)		
$\hat{B}_D$	−0.922 (39.91)	−0.788 (24.02)
$\hat{B}_{DH}$	0.290 (48.08)	−0.614 (29.87)
$\hat{B}_{DHC}$	0.598 (49.76)	−0.723 (30.01)

$$\hat{B}_D = \beta_1 D^{\beta_2} \tag{1}$$

$$\hat{B}_{DH} = \beta_1 D^{\beta_2} H^{\beta_3} \tag{2}$$

$$\hat{B}_{DHC} = \beta_1 D^{\beta_2} H^{\beta_3} CR^{\beta_4} \tag{3}$$

where $\hat{B}_{[\cdot]}$ is the predicted total tree biomass (kg) using the indicated predictors, and β_{1-4} are estimated coefficients. Application of these models to the QA data resulted in two biomass predictions for the same tree, one based on the production data and another based on the audit data. A summary of distribution parameters for differences in measured variables by size class as well as predicted biomass from models 1–3 is given in Table 2. Given the relatively small mean differences, it was assumed the measurement differences were unbiased and the primary interest was in the standard deviation (SD) of the measurement differences. For later reference, these SDs will be denoted by $\hat{\sigma}_{Xijk}$ where j refers to the size classes for each variable shown in Table 2 and others as previously defined.

Measurement/Growth Analysis

Having summarized measurement variation and growth changes, the two elements were combined for analysis. An initial examination consisted of evaluating the mean rate of growth over the 5-year cycle length in the context of measurement variability. To accomplish this, the data summarized in Table 2 were further broken down into the species group/latitude band classes shown in Table 1 to provide mean growth and measurement SD information for each size class, latitude band, and species group combination. These data were then used to calculate weighted (by number of trees) means of each distribution parameter to develop distributions having the mean growth value and the SD of the measurements for each latitude band. The statistical notation was now simplified to the distribution mean of the variable of interest being $\hat{\mu}_{Xk}$ and the SD given by $\hat{\sigma}_{Xk}$.

Analyzing the distributions characterized by ($\hat{\mu}_{Xk}$,$\hat{\sigma}_{Xk}$) allows one to estimate the proportion of measurements at T2 that may turn out to be smaller than the corresponding T1 measurement even after 5 years of growth has occurred. More importantly, these distributions provide insight into how the degree of measurement variation affects the efficiency and effectiveness of the monitoring effort at various temporal scales. An extreme example would be a very short cycle length, e.g., 2 weeks per the audit remeasurement. Assuming no practical growth has occurred and measurements are unbiased, we would expect a mean difference of zero and a distribution of "growth" having the same distribution as measurement variation. As cycle lengths increase, the measurement variability remains the same, however, the growth increases such that the signal-to-noise ratio (SNR) increases. In this context, the SNR can simply be expressed as the reciprocal of the coefficient of variation (Groeneveld 2011). For this study, SNR would be given by $\hat{\mu}_{Xk}/\hat{\sigma}_{Xk}$. Having this information and assuming a normal distribution (which was generally supported by the data), it is straightforward to calculate the proportion of observations that would be expected to be negative for various cycle lengths. This allows the relationship between SNR and proportion of negative values to be elucidated.

While assessment of SNR and proportion of expected negative measurements for *D*, *H*, and *CR* is informative, it is of further

Table 3. Estimated coefficients and fit statistics for models 1–3 by species group. R^2 is proportion of variation explained by the model and RMSE is the square root of mean squared error.

Model	β_1	β_2	β_3	β_4	R^2	RMSE
B_D (Hardwood)	0.24819	2.17992	–	–	0.931	133.3
B_D (Softwood)	0.11563	2.31827	–	–	0.917	85.6
B_{DH} (Hardwood)	0.07045	2.00835	0.60623	–	0.950	113.3
B_{DH} (Softwood)	0.02330	1.81592	1.11546	–	0.968	53.6
B_{DHC} (Hardwood)	0.05614	1.99327	0.62127	0.06522	0.951	112.8
B_{DHC} (Softwood)	0.03087	1.85285	1.06014	−0.06851	0.968	53.2

interest to evaluate these metrics in the context of predicted biomass values from models 1–3. Thus, in a manner similar to the above formulation, the mean change in predicted biomass over the measurement interval is denoted $\hat{\mu}_{\hat{B}(\cdot)k}$, while the corresponding variability due to measurement variation in the input variables is given as $\hat{\sigma}_{\hat{B}(\cdot)k}$ where $\hat{B}_{[\cdot]}$, references the biomass models 1–3. SNR and the expected proportion of negative values were calculated as described above. In the analysis of differences in biomass predictions, there were a few instances where the SDs were particularly large due to an extreme measurement variation for some trees. When this occurred, it was difficult to determine if the difference was strictly due to measurement or whether some other type of error was involved, e.g., data entry mistake. To minimize the influence of these outliers and provide more representative statistics, Huber's (1964) method was used by setting values less than $-3\hat{\sigma}_{Xk}$ equal to $-3\hat{\sigma}_{Xk}$, setting values greater than $3\hat{\sigma}_{Xk}$ equal to $3\hat{\sigma}_{Xk}$, and then recalculating $\hat{\sigma}_{Xk}$. Observations affected by this method were 0.5, 1.2, and 1.6% for models 1–3, respectively.

Due to the differing rates of growth in each latitude band, the time period required to achieve a given SNR threshold was evaluated for each band and for each of the three biomass models 1–3 assuming a linear increase in growth. An examination of these relationships suggested appropriate cycle lengths for each band, depending on the complexity of the biomass model being employed.

Results

Biomass models 1–3 were intended to depict a range of model complexities that may be used in forest inventory applications. The nonlinear regression analysis provided estimated coefficients to be used in the prediction of individual tree biomass (Table 3). These models were fitted in the order listed under the assumption that variables would be included in the same manner, i.e., virtually every inventory has *D* measured, many will have both *D* and *H*, while some may have *D*, *H*, and *CR*. The results indicated that *D* alone explained a considerable amount of variation in biomass; however, the addition of *H* was useful in that the model R^2 was improved and root mean squared error was reduced by 15 and 37% for hardwoods and softwoods, respectively. The inclusion of *CR* provided little additional information once *D* and *H* were accounted for. It should be noted that the statistics provided in Table 3 are for comparative purposes only. The biomass values used in the regression analyses are predicted values from other models (Woodall et al. 2011) and therefore do not exhibit the range of variability that would be found in observed data.

The results showed that the measurements were, for practical purposes, unbiased (Table 2); however, the variability in measurements generally increased as tree size increased. It was also shown that the variability in predicted values of biomass increased as the number of predictor variables increased, suggesting the measurement variation in *H* translated into increased observer-to-observer variation in biomass prediction for the same trees. Minimal additional variation in predicted biomass due to measurement variation was incurred by adding *CR* to the model. These results reflected the combined impacts of measurement variation, inherent population variability, and the relative importance of the predictor variable(s) in the model.

Generally, we expect that tree size will increase from one measurement to the next. This is particularly applicable to *D*, *H*, and *B*; however, *CR* may increase, remain the same, or decrease depending on various factors such as tree age, stand density, and disturbance history. In these data, the expected trends were present with increases in mean *D* and *H* for all latitude bands (Table 1). For these variables, there was also a notable trend with latitude as tree growth was faster as latitude decreased; the exception being for the southernmost band below N 30 degrees. Changes in *CR* were less pronounced, with most being slightly negative and those with the largest differences occurring in the southern latitudes for softwood species.

To assess measurement variation in the context of growth rates, the mean growth $\hat{\mu}_{Xk}$ and SD of measurements $\hat{\sigma}_{Xk}$ were used to assess the proportion of measurements expected to be smaller at T2 than at T1. As *D* was the most consistent measurement of the three variables studied, the proportion of measurements expected to be smaller after 5 years of growth was quite low (Table 4) with the largest value being about 0.03 for hardwoods in the northernmost latitude band. Corresponding SNR values were also relatively high, with most values exceeding 2.0 and some softwoods in southern bands exceeding 4.0. Conversely, height measurements exhibited high variability; softwoods north of N 40 degrees latitude and all hardwoods had expected percentage of negative measurement differences in the 20–40% range with the higher values occurring in the northernmost bands where growth rates were slowest. Again fast-growing softwoods in a few of the southern bands were the notable exception, where only 1–3% of height measurements were expected to be smaller at T2 than T1. SNR values ranged from approximately 0.35 to 1.0 except for the southern softwoods that had values ranging from 1.5–2.3. Due to crown ratios generally getting smaller over the measurement period (Table 1), it was not surprising to see many expected proportions of negative measurement differences greater than 0.5. However, the crown measurements were also quite variable as the SNR values only ranged from 0.45 to 0.85.

For predicted biomass, the proportion of negative growth observations and SNR depended on model complexity. The simplest model using *D* alone had expected negative growth observations at less than 1% for all but the northernmost latitude band; however, all bands exhibited SNR exceeding 2.0. When adding *H* as an additional predictor, the proportion of negative observations increased

Table 4. **Proportion of expected negative measurement differences and signal-to-noise ratio (SNR) for diameter at breast height (D), total height (H), and crown ratio (CR), and proportion expected negative predicted biomass values and SNR for models 1–3 by species group and latitude band.**

Species group	Latitude degrees	D(SNR)	H(SNR)	CR(SNR)	B_D(SNR)	B_{DH}(SNR)	B_{DHC}(SNR)
Hardwood	>46	0.031 (1.87)	0.364 (0.35)	0.519 (0.05)	0.018 (2.11)	0.152 (1.03)	0.179 (0.92)
Hardwood	44–46	0.018 (2.10)	0.352 (0.38)	0.458 (0.11)	0.004 (2.65)	0.099 (1.29)	0.116 (1.19)
Hardwood	42–44	0.013 (2.23)	0.314 (0.48)	0.449 (0.13)	0.002 (2.91)	0.078 (1.42)	0.095 (1.31)
Hardwood	40–42	0.015 (2.16)	0.316 (0.48)	0.439 (0.15)	0.001 (3.18)	0.065 (1.52)	0.086 (1.37)
Hardwood	38–40	0.018 (2.10)	0.332 (0.43)	0.576 (0.19)	0.002 (2.93)	0.082 (1.39)	0.101 (1.28)
Hardwood	36–38	0.017 (2.13)	0.321 (0.47)	0.592 (0.23)	0.001 (3.14)	0.070 (1.48)	0.086 (1.37)
Hardwood	34–36	0.019 (2.07)	0.267 (0.62)	0.536 (0.09)	0.000 (3.35)	0.059 (1.56)	0.071 (1.46)
Hardwood	32–34	0.012 (2.27)	0.258 (0.65)	0.536 (0.09)	0.000 (3.36)	0.057 (1.58)	0.066 (1.50)
Hardwood	30–32	0.007 (2.43)	0.267 (0.62)	0.625 (0.32)	0.001 (3.26)	0.059 (1.56)	0.075 (1.44)
Hardwood	<30	0.009 (2.38)	0.335 (0.43)	0.578 (0.20)	0.003 (2.74)	0.096 (1.30)	0.136 (1.10)
Softwood	>46	0.020 (2.05)	0.264 (0.63)	0.536 (0.09)	0.015 (2.17)	0.186 (0.89)	0.195 (0.86)
Softwood	44–46	0.011 (2.29)	0.243 (0.70)	0.547 (0.12)	0.004 (2.66)	0.145 (1.06)	0.151 (1.03)
Softwood	42–44	0.019 (2.07)	0.195 (0.86)	0.513 (0.03)	0.004 (2.62)	0.157 (1.01)	0.161 (0.99)
Softwood	40–42	0.016 (2.15)	0.202 (0.83)	0.546 (0.12)	0.003 (2.75)	0.142 (1.07)	0.154 (1.02)
Softwood	38–40	0.007 (2.46)	0.164 (0.98)	0.739 (0.64)	0.000 (3.54)	0.094 (1.32)	0.106 (1.25)
Softwood	36–38	0.000 (3.60)	0.066 (1.51)	0.666 (0.43)	0.000 (6.57)	0.009 (2.36)	0.009 (2.36)
Softwood	34–36	0.000 (4.42)	0.022 (2.01)	0.680 (0.47)	0.000 (8.40)	0.001 (3.00)	0.001 (3.03)
Softwood	32–34	0.000 (5.11)	0.010 (2.31)	0.725 (0.60)	0.000 (9.76)	0.000 (3.43)	0.000 (3.48)
Softwood	30–32	0.000 (4.95)	0.011 (2.30)	0.859 (1.08)	0.000 (9.39)	0.001 (3.28)	0.000 (3.33)
Softwood	<30	0.000 (3.50)	0.032 (1.85)	0.725 (0.60)	0.000 (7.12)	0.005 (2.57)	0.007 (2.47)

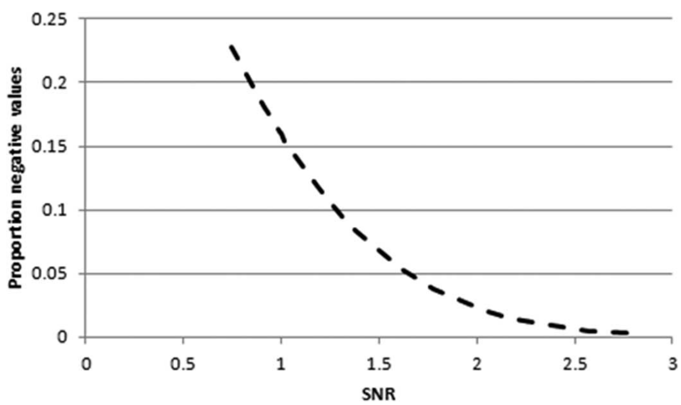

Figure 2. Relationship between proportion of negative values and SNR assuming a normal distribution.

dramatically, ranging from roughly 6–19% with the exception of the fast-growing southern softwoods. While these softwoods had less than 1% expected negative observations, the addition of H to the model resulted in roughly 60% decreases in SNR. Due to the relatively small influence of CR in model 3, the statistics were only slightly worse than those when CR was not included.

From a biomass estimation perspective, it is desirable to have growth over the inventory cycle exceed the noise due to measurement variability. Because the proportion of negative measurement differences can be computed from the components of SNR, the relationship between the proportion of negative measurements and SNR is easily established (Figure 2). This allows for determination of the SNR needed to limit the number of negative differences in predicted tree biomass to an acceptable level. As such, the minimum cycle length necessary to attain the desired SNR can be specified in relation to growth rate and biomass model complexity.

Due to the mixed species composition found in the study region, assessment of inventory cycle lengths were considered across all trees occurring in each latitude band. The relationship of SNR to latitude band at various cycle lengths is shown in Figure 3 for the three levels of biomass model complexity 1–3. Generally, greater SNR was associated with increasing cycle length. When comparing among biomass models, the model using only D as a predictor had the strongest SNR of the three models, particularly in the southern latitudes, where SNR exceeded 10 for 10-year cycle lengths. The SNR was substantially weaker for models 2 and 3, with maximum values only approaching 5 for 10-year cycles. These models exhibited similar results due to the CR variable having little influence on the predicted biomass values; however, the additional measurement variation in CR caused model 3 to have slightly reduced SNR. These results can be used to evaluate various scenarios of efficiency. For example, the acceptable maximum number of negative biomass growth observations was assumed to be 5%. The relationship depicted in Figure 2 suggested that the corresponding SNR was approximately 1.7. Now assuming the biomass prediction model relied on D only (Figure 3A), the horizontal line at SNR = 1.7 suggested that a cycle length of 3 years was possible for latitudes below N 38 degrees. However, a cycle length of 5 years would be better suited to latitudes north of N 38 degrees. The same logic applied to assessments for models 2 and 3, where shifts to longer cycle lengths were indicated for these more complex models (Figure 3B and C). For instance, a minimum cycle length of 5 years was proposed in the southern most latitudes, while 10-year cycles were the prescribed minimum for the two northernmost bands. Results for negative observation thresholds other than 5% can be approximated by computing the minimal SNR for the chosen threshold and placing the corresponding horizontal line in Figure 3A–C.

Discussion

Data collection on forest inventory sample plots is often a substantial portion of the total inventory cost. When monitoring change, it is important that growth trends occurring in the population can be ascertained. Selection of an appropriate measurement cycle length is crucial as cycles that are too short may have inconsequential growth in relation to measurement variation in key attributes. Of the three variables analyzed in this study, D exhibited a relatively small amount of variation in comparison to H and CR, and this was expected due to the differences in difficulty for obtaining

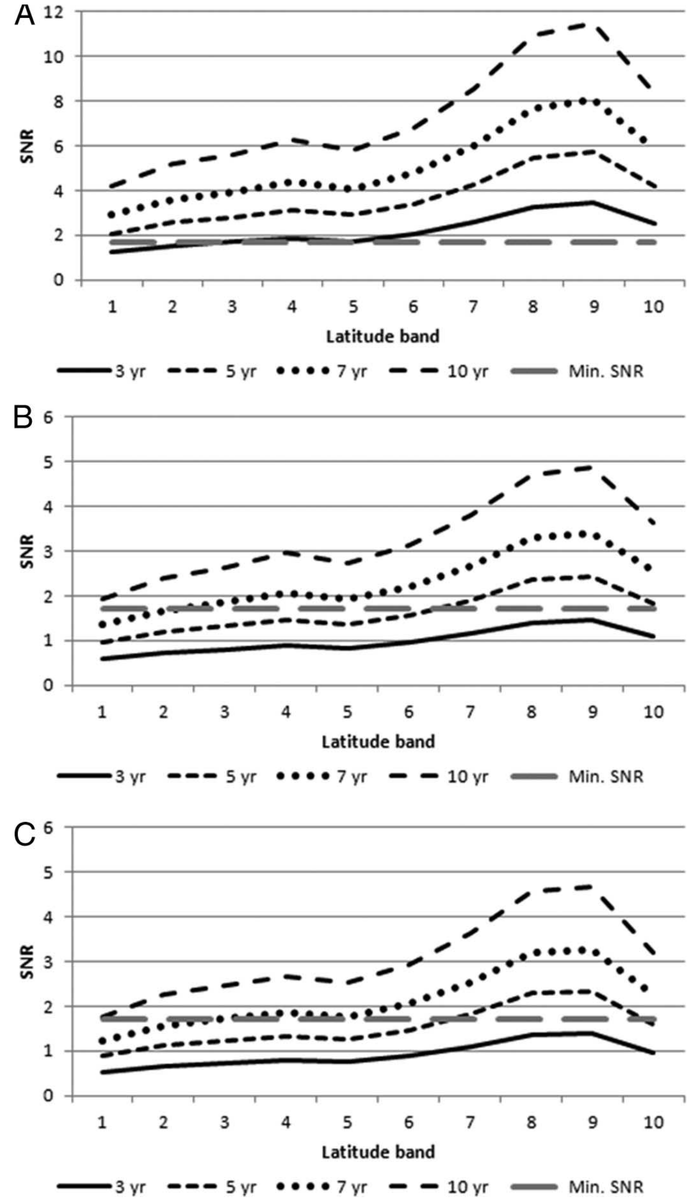

Figure 3. Relationship between SNR and latitude band for 3-, 5-, 7-, and 10-year cycle lengths using (A) biomass model 1, B_D, (B) biomass model 2, B_{DH}, and (C) biomass model 3, B_{DHC}. The horizontal line at SNR = 1.7 depicts a threshold of 5% negative predicted biomass values.

these measurements. A primary factor contributing to the variability of *H* and *CR* is the inability to view tree tops in mature, closed-canopy stands that are prevalent in the region. Measurement variation will always be present, and it is essential that the magnitude of variation is empirically quantified, as it is often larger than anticipated. The FIA program expends considerable effort in training and certification of field crews, which suggests the amounts of variation found here is near the minimum attainable in these forests.

As biomass model complexity increased, the corresponding SNR decreased because of the above-mentioned measurement variation in *H* and *CR*. This suggests a thought-provoking paradox between model accuracy for individual trees and estimation of population parameters. As shown in Table 3, notably improved biomass prediction accuracy for individual trees was obtained when *H* was added as a second predictor variable in model 2. However, the use of model 2 also resulted in substantial decreases in SNR and suggested longer cycle lengths. Thus, for population estimates, using only *D* as a predictor was preferable. Inventory managers need to assess the relative importance of individual tree accuracy in the context of population-level SNR. Additionally, it was shown that adding *CR* did little to improve biomass prediction accuracy for individual trees. The measurement variation due to CR resulted in a further decrease in SNR. This outcome indicated using biomass prediction models having input variables that only marginally contributed to prediction accuracy and also exhibited appreciable measurement variation was counterproductive.

The analysis of growth rates as represented by latitude bands clearly indicated that substantial differences in SNR are present in the study area. This was particularly notable for the softwood species group in the N 30–38 degrees latitude range. This portion of the study area has millions of acres in intensively managed, fast-growing plantations, and it is not surprising the highest rates of growth were found here. Consequently, it is in this area that the shortest cycle lengths can be implemented while maintaining sufficient SNR. However, there was also evidence that moving southward in latitude does not always equate to increases in SNR. These data consistently showed a decline in SNR for the southernmost latitude band (< N 30), suggesting other factors such as species range limits may influence the outcome other than growing season length alone. Eastern cottonwood, black cherry, red maple, loblolly pine, beech, and many oak and hickory species are growing near the southern edge of their range at N 30 degrees latitude (Harlow et al. 1991), which suggests that these trees may grow more slowly here. Finally, forests in the northern latitudes tend to have relatively slow growth in comparison to more southern locations due to lower temperatures and shorter growing seasons. Other factors contributing to low growth rates include the increasingly mature status and associated slowing of growth in many northern forests, as well as a similar phenomenon suggested for the far south, i.e., species growing on the edge of their natural range (e.g., balsam fir). This portion of the study area has the longest prescribed cycle lengths, as rates of growth and SNR continue to decrease with increasing northern latitudes.

The primary focus of this paper was to examine how measurement variation and growth rates can inform cycle lengths such that the number of negative measurement differences is kept to a minimum. Therefore, it should be noted that cycle lengths suggested by these results do not imply that statistically significant trends in population estimates will be realized. In many inventories, the sample plot is the primary sampling unit and the variance of the estimate derives from among-plot variation. Other factors that influence the ability to detect change include plot design, sample size, effect size, and chosen level of confidence to avoid Type I errors (Foster 2001). To evaluate the ability to detect changes in the population, it is recommended that power analyses be undertaken (Westfall et al. 2013).

The results reflect the environmental conditions and population structure present during the time period. Future conditions could change the relationships found here if there was a substantial deviation from current status. For example, extended drought in the south could reduce the SNR for the fast-growing plantation softwoods. Similarly, increased harvest rates of mature stands in the north that result in younger, faster-growing forests could increase SNR. Clearly, there are numerous scenarios that could be envisioned, and the effects on SNR would be largely speculative without empirical validation. In this study, it was assumed that growth rates were linear, e.g., the growth over 10 years would be two times the growth over 5 years. However, other potential trajectories could be evaluated. For example, Van Deusen (2002) simulated flat, linear increasing, and quadratic growth scenarios in the context of estimating population trends. The effects on SNR and associated cycle lengths for these alternative growth trajectories are an area for further study.

This study employed latitude bands to provide a spatial framework for growth rates. More complex analyses could be undertaken that also include other factors likely to affect growth rates such as elevation and climatic information (e.g., temperature and precipitation). Further refinement of the results would likely increase inventory efficiency as subareas within latitude bands where differing cycle lengths might be appropriate could be identified. However, these further refinements could also make the inventory more difficult to implement. For example, FIA has traditionally implemented the inventory and reported resource statistics at the state level. Enhancement of the analyses to include further refined areal subdivisions may result in within-state areas that have different cycle lengths. This would clearly have implications regarding fieldwork and data storage, processing, analysis, and interpretation under the current database configuration and reporting paradigm.

While adopting cycle lengths that have appropriate SNR will result in more efficient and effective forest inventories, adjustments to current practices may be needed. Potential issues that may arise include: (1) personnel requirements—a change in plot production rates may necessitate an increase/decrease in the workforce, (2) database modifications—altering current cycle lengths will change the plot cohorts that are assigned to certain measurement years, and (3) various analytical considerations—such as creating temporarily altered remeasurement regimes as some plots are reassigned to cohorts corresponding to the new cycle length. A balanced reassignment of such plots would result in some plots having remeasurement periods as short as 1 year. Clearly, this is not desirable as these plots would exhibit low SNR. Thus, the impacts on all aspects of the inventory program need to be considered in the decisionmaking process.

Finally, a note regarding measurement variation is warranted. The QA effort is designed to quantify the amount of variability in measurements over a number of field crews. A key point is that bias cannot be assessed with these data as the true values are unknown. When measurements are taken on inventory plots over time, the measurement variability results in some observations being smaller than the previous measurement in spite of any growth over the remeasurement period. What is commonly overlooked is there is also a group of measurements for which the difference is considerably larger than would be expected, i.e., measurement variation works in both directions. It is easy to condemn measurements that are smaller; however, it is much more difficult to identify those that are egregiously larger. If efforts to correct data are not applied equally to both sides of the measurement variation issue, bias will almost surely result. Furthermore, such efforts would require assumptions regarding which measurement is more accurate even though the true values are unknown. As such, it is better to endeavor to minimize measurement variation via training, consistent equipment calibration, and field crew retention (same crew measuring same plot over time) than to employ methods that may cause crews to alter their observations due to previous measurement values.

Conclusion

It is often the case that forests do not change very quickly. While there is a legitimate need for up-to-date information on forest resources such that effective management and policy decisions can be implemented, there are also practical limitations for repeatedly conducting forest inventories within a short time frame. Apart from the nearly ubiquitous constraint of available financial resources, obtaining measurements of sufficient accuracy in relation to the magnitude of change in the population can be challenging. Furthermore, the repeatability of certain measurements can vary considerably depending on numerous factors. This measurement variation propagates through biomass prediction models as well. In this study, it was found that biomass models using D alone provided the best SNR; however, more complex models provided better individual tree biomass prediction. Inventory managers should evaluate such tradeoffs when selecting models to employ.

Generally, populations exhibiting relatively rapid change can be continually measured on short cycle lengths. For the southern latitudes comprised primarily of fast-growing softwoods, revisits every 3–5 years can be reasonable. However, forests in northern latitudes should not be revisited so frequently as slower growth rates require longer time periods to attain sufficient SNR. Inventory managers should consider the concepts and results presented in this paper when making decisions regarding cycle lengths. It is acknowledged that this analysis is based on tree growth rates only and there may be other factors in establishing cycle lengths, such as the need to address land-use change issues, estimate effects of catastrophic events, and/or fulfill legislative mandates.

Literature Cited

BECHTOLD, W.A., AND P.L. PATTERSON (EDS.). 2005. *The enhanced Forest Inventory and Analysis program—National sampling design and estimation procedures.* USDA For. Serv., Gen. Tech. Rep. SRS-80, Southern Research Station, Asheville, NC. 85 p.

BRASSEL, P., AND H. LISCHKE (EDS.). 2001. *Swiss national forest inventory: Methods and models of the second assessment.* Swiss Federal Research Institute WSL, Birmensdorf, Switzerland. 336 p.

FOSTER, J.R. 2001. Statistical power in forest monitoring. *For. Ecol. Manage.* 151(1–3):211–222.

GILLESPIE, A.J. 1999. Rationale for a national annual forest inventory program. *J. For.* 97(12):16–20.

GILLIS, M.D., A.Y. OMULE, AND T. BRIERLEY. 2005. Monitoring Canada's forests: The national forest inventory. *For. Chron.* 81(2):214–221.

GROENEVELD, R.A. 2011. Influence functions for the coefficient of variation, its inverse, and CV comparisons. *Comm. Stat. Theory Meth.* 40(23):4139–4150.

HARLOW, W.M., E.S. HARRAR, J.W. HARDIN, AND F.M. WHITE. 1991. *Textbook of dendrology,* 7th ed. McGraw-Hill Book Co., New York. 501 p.

HUBER, P.J. 1964. Robust estimation of a location parameter. *Ann. Math. Statist.* 35(1):73–101.

MANIATIS, D., AND D. MOLLICONE. 2010. Options for sampling and stratification for national forest inventories to implement REDD+ under the UNFCCC. *Carb. Bal. Manage.* 5:9. doi:10.1186/1750-0680-5-9.

POLLARD, J.E., J.A. WESTFALL, P.L. PATTERSON, D.L. GARTNER, M.H. HANSEN, AND O. KUEGLER. 2006. Forest inventory and analysis national data quality assessment report for 2000 to 2003. USDA For. Serv., Gen. Tech. Rep. RMRS-181, Rocky Mountain Research Station, Fort Collins, CO. 43 p.

SÖDERBERG, U. 2000. Designing a sample-based National Forest Inventory for Denmark. Outline of the sample-based National Forest Inventory. Danish Forest and Landscape Research Institute, Rep. No. 2, Hørsholm, Denmark. 27 p.

TOMPPO, E. 2006. The Finnish National Forest Inventory. P. 179–194 in *Forest inventory: Methodology and applications,* Kangas, A., and M. Maltamo (eds.). Springer, Dordrecht, The Netherlands.

TOMPPO, E., T. GSCHWANTNER, M. LAWRENCE, AND R.E. MCROBERTS (EDS.). 2010. *National forest inventories-pathways for common reporting.* Springer, New York. 612 p.

USDA FOREST SERVICE. 2007. Forest inventory and analysis national core field guide, volume 1: Field data collection procedures for phase 2 plots, version 4.0. USDA For. Serv., Internal Rep., Forest Inventory and Analysis, Arlington, VA.

VAN DEUSEN, P.C. 2002. Comparison of some annual forest inventory estimators. *Can. J. For. Res.* 32(11):1992–1995.

WESTFALL, J.A. (ED.). 2009. *FIA national assessment of data quality for forest health indicators.* USDA For. Serv., Gen. Tech. Rep. NRS-53, Northern Research Station, Newtown Square, PA. 80 p.

WESTFALL, J.A., C.W. WOODALL, AND M.A. HATFIELD. 2013. A statistical power analysis of woody carbon flux from forest inventory data. *Clim. Change* 118(3–4):919–931.

WOODALL, C.W., L.S. HEATH, G.M. DOMKE, AND M.C. NICHOLS. 2011. *Methods and equations for estimating aboveground volume, biomass, and carbon for trees in the US forest inventory, 2010.* USDA For. Serv., Gen. Tech. Rep. NRS-88, Northern Research Station, Newtown Square, PA. 30 p.