USDA United States
Department
of Agriculture

Forest Service

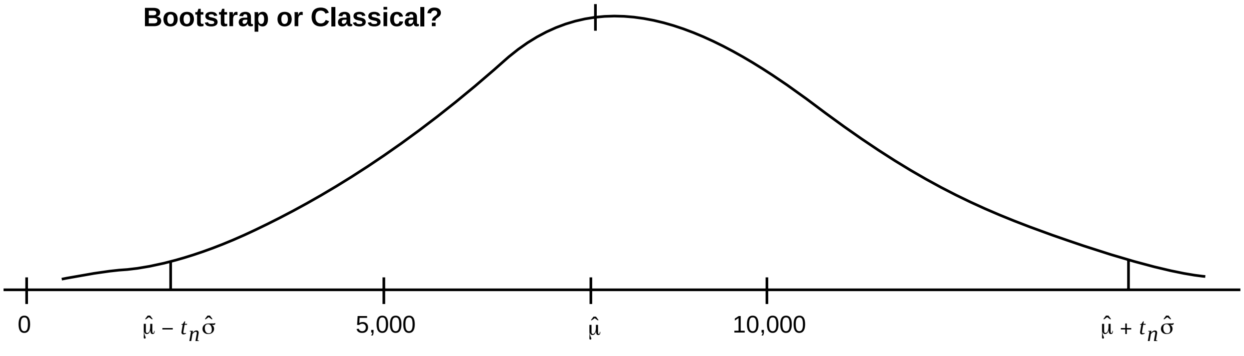
Rocky Mountain
Research Station

General Technical
Report RMRS-GTR-57

August 2000

Reliability of Confidence Intervals Calculated by Bootstrap and Classical Methods Using the FIA 1-ha Plot Design

H. T. Schreuder
M. S. Williams



Abstract

Schreuder, H. T.; Williams, M. S. 2000. **Reliability of confidence intervals calculated by bootstrap and classical methods using the FIA 1-ha plot design**. Gen. Tech. Rep. RMRS-GTR-57. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 6 p.

In simulation sampling from forest populations using sample sizes of 20, 40, and 60 plots respectively, confidence intervals based on the bootstrap (accelerated, percentile, and t-distribution based) were calculated and compared with those based on the classical t confidence intervals for mapped populations and subdomains within those populations. A 68.1 ha mapped population, constructed out of 0.081 ha (1/5 acre) Forest Inventory and Analysis of the USDA Forest Service (FIA) plot measurements at 2 points of time in Maine, United States and a 64 ha mapped population from Surinam, South America with only one measurement, were used. The plot designs used were the FIA plot consisting of a 1-ha circular plot subsampled by four 0.0169 ha (1/24 acre) subplots, a 0.081 ha plot that was used in the north east by FIA, and a 10-point cluster of VRP plots that was used in the north central by FIA.

The confidence intervals of all estimates, even those from a sample of size 60, failed to meet the nominal 95% standard. Of the 4 methods used to derive the intervals, the classical method was consistently best in terms of achieved confidence level. This was followed by the three bootstrap methods: t-distribution based, accelerated, and percentile.

We recommend use of the classical t confidence intervals even for small sample sizes and less common attributes. If the classical standard error cannot be computed easily, the t-distribution based bootstrap should be used since it gives only slightly less reliable confidence levels. Also, the bootstrap standard error can often be computed in situations where the classical standard error cannot be.

Keywords: FIA plot, subdomains, simulation study, mapped populations, fixed-area sampling

The Authors

H. T. Schreuder and M. S. Williams are Mathematical Statisticians, Rocky Mountain Research Station, USDA Forest Service, located at the Natural Resources Research Center, 2150 Centre Avenue, Building A, Fort Collins, CO 80526.

You may order additional copies of this publication by sending your mailing information in label form through one of the following media. Please specify the publication title and number.

Telephone	(970) 498-1392
FAX	(970) 498-1396
E-mail	rschneider@fs.fed.us
Web site	http://www.fs.fed.us/rm
Mailing Address	Publications Distribution Rocky Mountain Research Station 240 West Prospect Road Fort Collins, CO 80526

Reliability of Confidence Intervals Calculated by Bootstrap and Classical Methods Using the Fia 1-Ha Plot Design

H. T. Schreuder
M. S. Williams

Contents

Introduction

Dale Robertson (1993), Chief of the USDA Forest Service (FS) ordered mapped designs (ground plots mapped for the forest conditions and ecotones within them) be used by all Forest Inventory and Analysis (FIA) units in their inventories and on National Forest System lands.

In the Forest Health Monitoring program (FHM) of the FS, a cluster of 4 fixed-area circular subplots are used to sample a circular 1-ha plot[1]. These subplots (radius of 7.32 m = 24 ft) are mapped for forest conditions (Messer et al. 1991, Scott et al. 1993). This official FIA plot design is favored over a similar one involving variable radius plot (VRP) sampling (Hahn et al. 1995) that was considered earlier. Estimation theory for the design is given in Williams and Schreuder (1995) and Scott and Bechtold (1995).

Previously, the northeastern FIA unit of the FS (NE FIA) used a 0.081 ha (1/5-acre) circular plot (radius = 57.2 ft) at each location. The other FIA units used a 5 or 10-point cluster of VRP plots.

Little or no work has been done to evaluate the reliability of confidence intervals for estimating forest parameters as conducted by FIA. The primary objective of the FIA program is to produce estimates of forest attributes such as total volume and number of trees and change in such attributes over time for large regions of the United States. For these common attributes, the assumption of normality approximated by the t-distribution should be reasonable and the nominal coverage rates will generally be achieved even for fairly small sample sizes. But, often users are interested in generating estimates for subpopulations or for subdomains, where the latter are subpopulations known for the sampled but not for the unsampled units of the original data set.

An excellent example of this is the subdomain represented by the screened plots used to establish a possible growth decline in Georgia and Alabama. This situation occurred in the mid 1980s. A series of studies (Gadbury et al. 1998, Ueng et al. 1997, Zeide 1992, and references therein) debated whether the growth of naturally occurring, undisturbed stands of various pine species had declined from the period of 1962-1972 to the period of 1972-82. As noted in Casady et al. (1998), confidence intervals for subdomains constructed along traditional (classical) lines can lead to serious undercoverage; a fact not always appreciated in the literature. In forestry, confidence intervals for subdomain estimates constructed from traditional asymptotic theory can be subject to serious undercoverage because the assumption of normality is not even remotely satisfied by the distribution of subdomain estimates. This is particularly true for those that are a mixture of 0 estimates with extremely skewed continuous distribution (e.g. plot mortality estimates).

The objective of this study was to compare the classical and 3 types of bootstrap methods for estimating confidence intervals at a given nominal (95%) level for the standard FIA, the north east (NE) 0.081 ha and the north central (NC) 5-point VRP plots. We evaluated the reliability by coverage rate since we wanted high confidence that the statements made were correct. A 68.1 ha mapped population constructed for 2 points of time from original FIA 1/5 acre plots in Maine and a 60 ha Surinam population mapped at one point of time were used. The bootstrap methods are the percentile bootstrap, the t-distribution based bootstrap, and the accelerated bootstrap methods, which are described later.

Literature Review

Current objectives for FIA are to generate descriptive statistics, detect changes in such statistics, and analyze the data to identify, and possibly establish, cause-effect relationships (Schreuder and McClure 1991). Analytical inference using forest-survey data is becoming more important and requires examination of confidence intervals, which is the common way of testing significance of hypotheses with survey data. Use of survey data to establish cause-effect relationships is controversial (Schreuder and Thomas 1991), but such data have been used to identify possible cause-effect relationships in epidemiology (Feinstein 1988). Schreuder and McClure (1991) suggest modifications of the FIM designs to improve change detection and identify possible causes of change.

Such change in objectives to analytical inference forces more reliable estimation of confidence intervals and confidence levels for hypotheses testing. At the same time, new methods, such as the bootstrapping methods described below, offer exciting new possible solutions to reliable confidence interval estimation. Efron and Tibshirani (1993) define the bootstrap as a computer-based method to assign measures of accuracy to statistical estimates. They note (p.160) that with the bootstrap method accurate confidence intervals can be constructed without making normal theory

---

[1] FIA units now often consider the 4 subplots to be the actual plot.

assumptions. Bootstrapping also does not have symmetric confidence intervals when the distribution of possible estimates may not be symmetric, as is often the case with subdomain estimates. This is especially important when the goal of the inference is to determine the sustainability of a resource. In this case, the test of hypothesis determines whether 0 is included in the confidence interval (see for example Williams 1998 for subdomain change estimates).

The bootstrap t-method from Efron and Tibshirani, 1993 builds a table of bootstrap t-values. B bootstrap samples are generated and used to compute the bootstrap version of t for each. The bootstrap table consists of the percentiles of these B values with the lower $\alpha/2$ and upper $\alpha/2$ percentage of the values eliminated. Efron and Tibshirani recommend against this method because it can give erratic results, can be heavily influenced by a few outliers, and better bootstrap methods are available.

In the percentile interval method of bootstrapping (Efron and Tibshirani 1993), B bootstrap estimates $\hat{\theta}^*$ are generated. If $G(\hat{\theta}^*)$ is the cumulative distribution function of $\hat{\theta}^*$, then the percentile interval is:

$$(\hat{\theta}_{lo},\hat{\theta}_{up}) = (\hat{\theta}^{*(\alpha/2)},\hat{\theta}^{*(1-\alpha/2)}) = [\hat{G}^{-1}(\alpha/2),\hat{G}^{-1}(1-\alpha/2)]$$

for coverage $1-\alpha$ where $\hat{\theta}^{*(\alpha/2)}$ indicates the $100.\alpha/2th$ percentile of B bootstrap replications.

$$\hat{\theta}^*(1),\hat{\theta}^*(2),\ldots,\hat{\theta}^*(B)\cdot$$

Efron and Tibshirani note that the bootstrap-t intervals have good theoretical coverage probabilities but tend to be erratic in practice. The percentile intervals are less erratic but have less desirable coverage properties. We eliminated the bootstrap-t procedure from consideration after some preliminary simulations showed it to perform quite poorly.

A method that corrects for bias due to non-normality and accelerates convergence to a solution by correcting for the rate of change of the normalized standard error of $\hat{\theta}$ relative to the true parameter θ in constructing the confidence limits of the percentile interval method is called BCa. This method yields substantially improved limits in both theory and practice although the accuracy of the actual confidence level can still be erratic for small sample sizes (Efron and Tibshirani 1992). This method is accurate and unaffected by transformations. The BCa interval with desired coverage $1-\alpha$ is:

$$(\hat{\theta}_{lo},\hat{\theta}_{hi}) = (\hat{\theta}^{\alpha 1},\hat{\theta}^{\alpha 2}), \text{where}$$

$$\alpha 1 = \varphi\{\hat{z}_0 + (\hat{z}_0 + z^{(\alpha/2)})/(1-\hat{a}(\hat{z}_0 + z^{(\alpha/2)}))\}$$

and

$$\alpha 2 = \varphi\{\hat{z}_0 + (\hat{z}_0 + z^{(1-\alpha/2)})/(1-\hat{a}(\hat{z}_0 + z^{(1-\alpha/2)}))\}$$

where $z^{(.)}$ is the (.) percentile of the standard normal. The bias correction term $\hat{z}_0$ is obtained by computing the proportion of bootstrap estimates less than the original estimate $\hat{\theta}$, say pB, and then computing:

$$\hat{z}_0 = \varphi^{-1}(pB)$$

where φ^{-1} is the inverse function of a standard normal cumulative distribution function. The acceleration is:

$$\hat{a} = [\sum_{i=1}^{n}(\hat{\theta}_{(.)}-\hat{\theta}_{(i)})^3]/6[\sum_{i=1}^{n}(\hat{\theta}_{(.)}-\hat{\theta}_{(i)})^2]^{3/2}$$

where the $\hat{\theta}_{(i)}$ and $\hat{\theta}_{(.)}$ are the ith and average jackknife estimates of the parameter, and $\hat{\alpha}$ is the acceleration because it measures the change of the standard error of $\hat{\theta}$ relative to the value θ. This method has two advantages. One advantage is that this method is unaffected by transformations so that the BCa endpoints transform correctly if the parameter of interest θ is changed to some function of θ. A second advantage to this method is that the BCa intervals are second order accurate (i.e., their errors in matching the true confidence levels go to 0 as a function of $1/n$ as opposed to the bootstrap-t and percentile methods which are of order $1/\sqrt{n}$). This means that BCa gives better approximations of exact endpoints if they exist. Efron and Tibshirani do not discuss the use of the standard t-distribution with the bootstrap estimator of standard error considered here, called the t-distribution based bootstrap. This method uses the classical estimator for θ with the bootstrap standard error.

Efron and Tibshirani also discuss what they call the ABC bootstrap method, which eliminates the problem of excessive computations as required in the BCa method. The ABC method uses Taylor series expansions for approximations so that the estimates may break down occasionally, principally for non-smooth statistics such as the sample median. Since we want a robust procedure not subject to occasionally dubious results, and since the number of computations generally should not be a concern for our applications, we do not consider the ABC procedure here.

Smith (1997) evaluates the use of bootstrap confidence limits for groundfish trawl survey estimates of average abundance. In such surveys, stratified sampling is often used to monitor groundfish populations. The small sample sizes used and the skewed data characteristics of the variable of interest may be appropriate for the classical large sample properties of such estimates. Simulation results show that the percentile bootstrap limits were close to the expected values and that the bias, corrected and accelerated bootstrap confidence limits, can overcorrect for the data.

Methods

Random samples were drawn from mapped populations using a random number generator described in Kahaner et al. (1988), and the confidence limits at the nominal 95% confidence level were determined for the classical and 3 bootstrap methods in estimating a series of parameters. We focused on small sample sizes because all methods considered should work well for large sample sizes where asymptotic results are relevant and because FIM and similar surveys often have sample sizes of 30 or less due to considerable post-stratification.

Materials and Methods

The following populations were used in the simulations:

Maine: this consists of 841 mapped circular 0.081 ha (1/5 acre) plots for which tree measurements were recorded at 2 time periods. These plots were combined judiciously to give a square population of 68.1 ha using the transformation described by Williams et al. (2000). The population was divided into 3 distinct forest types, softwood, hardwood, and mixed softwood-hardwood. A plot was classified as either hardwood or softwood if 75% or more of the trees in it fell into one of the 2 categories, otherwise it was classified as mixed hardwood-softwood. The mix of hardwoods and softwood trees changed in the interval between measurements resulting in change in forest type. Plots were arranged within the 68.1 ha square to separate the population into 6 stands (2 each of hardwood, softwood, and mixed hardwood-softwood).

Surinam: this comprised a 60-ha (1500 x 400 m) section of a forest in Surinam, South America mapped by a group of students of S.G.Banyard (Schreuder et al. 1987) at the International Institute for Aerial Survey and Earth Sciences ITC in Enschede, Netherlands. The coordinates of all 6806 trees were digitized with a mechanical digitizer to the nearest 0.1 m and recorded on a computer-compatible tape along with tree diameters and species.

For the simulation, we drew a series of 4000 samples of size 20, 40, and 60 using randomly selected point centers as a starting point for all 3 plot designs. For Maine, we focused on the parameter estimates of the initial number of trees (N_1), change in number of trees (ΔN), basal area (BA), basal area growth (S) as estimated by the Van Deusen estimator (Schreuder et al. 1993, p.145) , mortality (M), and removals (R) using Horvitz-Thompson type estimators as described in Williams and Schreuder (1995). This was done for the population and also for subdomains of seedling-saplings, pole timber, and sawtimber-size trees. For Surinam, estimates were generated for number of trees and basal area for the population and for 3 species groups selected such that groups 1 and 2 were common and group 3 was rare.

The methods are denoted by Cl for classical, Bt for bootstrapping using the standard t distribution, Bp for the percentile bootstrap, and BCa for the accelerated bootstrap.

Results and Discussion

We show only the results for the FIA plot design since the other plot designs add little to the results. On average these plot designs provide slightly worse results than the FIA plot in terms of confidence-level cover rates. We show the results for one subdomain and for the overall population. The width of the standard bootstrap confidence intervals are almost always the shortest, those for the accelerated bootstrap next, with those for the classical t confidence intervals being almost always the widest. This is why the actual confidence levels for the classical estimation are usually the most reliable.

Maine results (table 1 and figures 1 through 4):

1. The 95% nominal confidence level is almost never reached by any of the 4 estimation techniques.
2. The classical confidence levels are almost always better than for the t-distribution based bootstrap, which is almost always better than the accelerated bootstrap, which is usually better than the percentile bootstrap.
3. The actual coverage rate approaches the nominal value generally, as one goes from n=20 to n=40 to n=60 (except for Cl, Bt, and Bp with S). But even for n=60, the actual is still often below the nominal level and this is particularly true for the more rare variables (mortality, removals, and other attributes not shown).

Table1—Actual and 95% nominal confidence levels for 3 sample sizes and 4 estimation methods for 1 domain and for the entire population for Maine and Surinam South America; 4000 samples, 4000 bootstrap samples.

		Maine sample size					
Parameter	**Method**	**20 Hardwood**	**20 All**	**40 Hardwood**	**40 All**	**60 Hardwood**	**60 All**
$\hat{N}$	Cl-*2	92.9	94.3	93.7	94.6	94.8	94.8
	Bt	92.5	93.6	93.3	94.3	94.7	94.6
	Bp	92.4	92.4	91.9	93.7	94.6	94.1
	Bca	93.8	92.6	93.7	94.0	94.8	94.6
$\Delta\hat{N}$	Cl	93.4	94.2	94.8	94.0	95.0	94.2
	Bt	93.0	93.4	94.5	93.7	94.8	93.9
	Bp	91.2	91.9	93.7	93.1	94.3	93.8
	BCa	91.3	92.7	93.8	93.4	93.9	93.9
$B\hat{A}$	Cl	93.8	94.8	94.9	94.4	94.7	94.5
	Bt	93.2	94.2	94.7	94.1	94.6	94.2
	Bp	92.7	92.5	94.5	93.4	94.7	94.0
	BCa	93.5	92.9	94.7	93.6	95.1	94.1
$\Delta\hat{S}$	Cl	92.7	95.1	94.7	94.6	94.8	94.4
	Bt	92.5	94.6	94.7	94.2	94.7	94.2
	Bp	90.4	94.6	93.1	93.5	93.8	93.8
	BCa	90.7	93.3	93.1	93.6	93.4	93.9
$\hat{M}$	Cl	88.3	93.4	91.6	93.9	92.0	93.9
	Bt	87.7	92.7	91.2	93.9	91.8	93.8
	Bp	87.9	91.2	91.6	93.3	92.0	93.3
	BCa	89.7	91.9	92.6	93.6	93.5	93.7
$\hat{C}$	Cl	85.4	91.5	90.0	93.0	91.8	93.0
	Bt	85.0	91.0	89.7	92.9	91.7	93.8
	Bp	85.3	90.2	90.4	92.5	92.2	93.6
	BCa	86.6	91.4	91.7	93.2	93.1	94.1
		Surinam sample size					
		20 Rare	**20 All**	**40 Rare**	**40 All**	**60 Rare**	**60 All**
$\hat{N}$	Cl	92.3	95.4	93.8	94.6	92.4	94.9
	Bt	92.0	94.8	93.1	94.3	92.4	94.9
	Bp	91.2	93.5	93.3	93.9	92.3	94.4
	BCa	90.7	93.6	90.7	94.0	91.3	94.5
$B\hat{A}$	Cl	90.0	93.8	92.6	94.4	92.6	94.2
	Bt	89.4	93.3	92.2	93.9	92.5	94.1
	Bp	89.5	91.9	92.3	93.1	92.4	93.6
	BCa	89.6	92.1	93.1	93.6	93.3	93.7

*2 Cl=classical,Bt=standard bootstrap, Bp=percentile bootstrap, Bca=accelerated bootstrap.

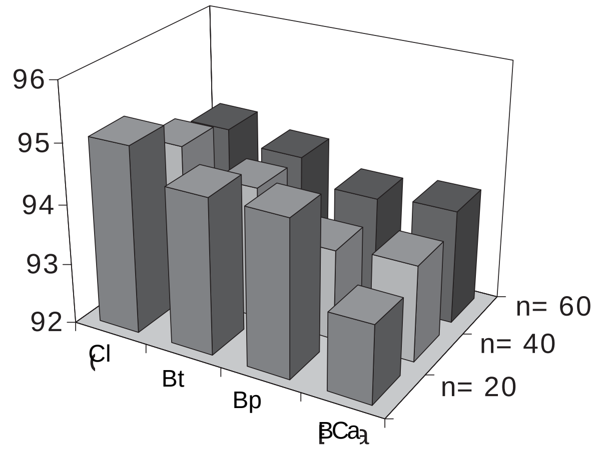


Figure 1—Percent coverage rates for survivor growth, $\Delta\hat{S}$.

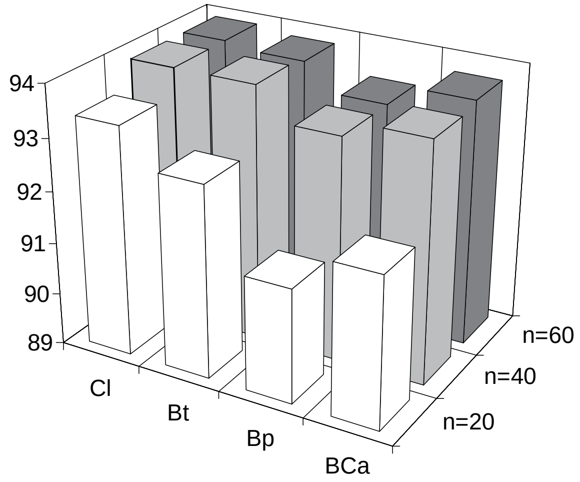


Figure 3—Percent coverage rates for number of trees $\hat{N}$.

Surinam results (table 1):

1. The classical confidence intervals are consistently best in terms of the closeness of the actual achieved confidence level to the nominal ones. This is true for all 3 sample sizes. The actual and nominal levels are generally very close but the actual improves only slightly, with increasing sample size; the actual is rarely above 95%.
2. The accelerated bootstrap method has better attained confidence levels than the percentile method. Specifically, the accelerated bootstrap is better in 55 cases, worse in 31, and tied 22 times relative to the percentile method.
3. The bootstrap actual confidence levels show a consistent improvement going from n=20 to n=40 to n=60. Even for n=60, the actual does not reach the nominal 95% level.
4. The confidence interval widths for the bootstrap methods are almost always narrower than for the classical method (not shown).
5. There is little difference between the 3 designs, but the FIM plot yields slightly higher actual confidence levels (not shown).

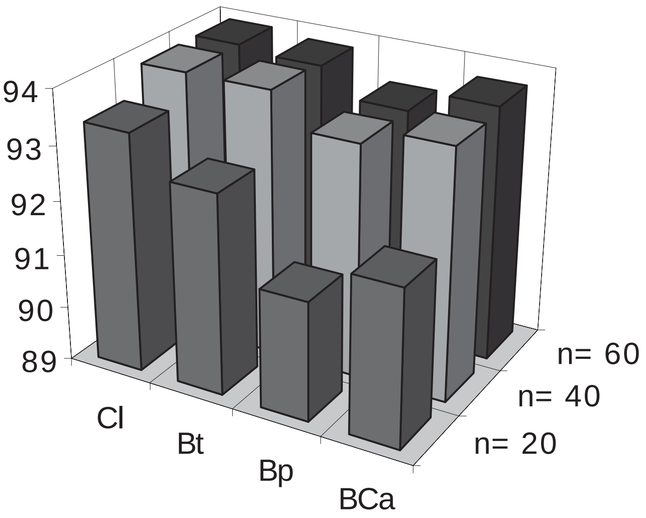


Figure 2—Percent coverage rates for mortaity, $\hat{M}$.

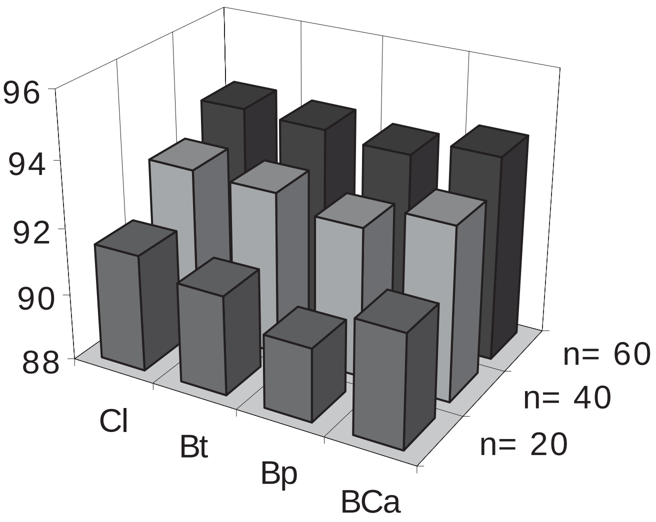


Figure 4—Percent coverage rates for removals, $\hat{C}$.

After reading the papers of DiCiccio and Efron (1996) and Efron and Tibshirani (1993), we had expected the accelerated bootstrap method of calculating confidence intervals to be superior to the other methods tested. But as these authors concede, this method can be erratic for small sample sizes where asymptotic results do not apply. Yet, such sample sizes are quite prevalent for many applications of FIA type data. Population Maine, as constructed, is extremely variable since these are FIA plots from across the entire state. But population Surinam is a real population and yielded basically the same results.

The great advantage of bootstrapping is that confidence intervals can be generated easily no matter how complex the actual sampling design is and the standard errors can be computed when it is difficult or impossible to compute classical standard errors. A further important advantage is that bootstrap confidence intervals tend to reflect the true nature of the sample distribution. Thus, the interval estimate will contain negative values only when the data give some indication that it is a real possibility, unlike the classical methods. Therefore, we feel that inference based on bootstrap methods is potentially more meaningful in spite of the inferior coverage rates. Given the advantages of bootstrapping, it is disappointing that these methods did not perform well with small sample sizes.

Summary

For the sample sizes considered, the results show rather conclusively that classical confidence intervals are more reliable than those for the bootstrap using the standard t-distribution, the accelerated bootstrap and the percentile bootstrap, in that order. If the classical standard error cannot be computed, the bootstrap with standard t-distribution is the method of choice. Actual coverage probabilities are close to the nominal 95% confidence levels for n=60 but clearly, improved methods are needed to attain it with a high degree of confidence. Bayesian methods (Cassidy et al. 1998) or saddle-point approximations, as successfully implemented in Li et al. (1995), may be the answer ultimately but, at present, they are difficult to implement.

Literature Cited

Casady,R.J., Dorfman, A.H. and Wang,S. 1998. Confidence intervals for domain parameters when the domain size is random. Survey Meth. 24:57-67.

DiCiccio, T.J. and Efron, B. 1996. Bootstrap confidence intervals. Stat. Sci 11:189-228.

Efron, B and Tibshirani, R.J. 1993. An Introduction to the Bootstrap. Chapman and Hall, NY. 436 p.

Feinstein, A. R. 1988. Scientific standards in epidemiologic studies of the menace of daily life. Science 242: 1257-1263.

Gadbury, G.L., Iyer, H.K., Schreuder, H.T. and Ueng, C.Y. 1998. A nonparametric analysis of plot basal area growth using tree based models. USDA Forest Service Rocky Mountain Res. Paper RMRS-RP-2.

Hahn, J. T., MacLean, C. D., Arner, S. L., and Bechtold, W. A. 1995. Procedures to handle FIA cluster plots that stradle two or more conditions. For. Sci. Monograph 31, 41:12-25.

Kahaner, D, Moler, C and Nash, S. 1988. Numerical methods and software. Prentice Hall, NY.

Li, J, Chen, M-C, Schreuder, H.T. and Gregoire, T.G. 1995. Forestry applications of saddle-point approximations to construct confidence intervals for population means. Biometrics 51: 61-72.

Messer, J. J., Linthurst, R. A., and Overton, W. S. 1991. An EPA program for monitoring ecological status and trends. Env. Monit. Assmt. 17: 67-78.

Robertson, F. D. 1993. Forest inventory plot rotation. USDA Forest Service, June 24, 1993 letter to Regional Foresters, Station Directors, Area Director, and IITF Director.

Schreuder, H. T. and McClure, J. P. 1991. Modifying forest survey procedures to establish cause-effect. Should it be done? Invited paper. IUFRO World Forestry Congress, Paris, France, Sept. 1991.

Schreuder, H. T. and Thomas, C. E. 1991. Establishing cause-effect relationships using forest survey data. For. Sci. 37: 1497-1525 (includes discussion).

Schreuder, H.T., Banyard, S.G. and Brink, G.E. 1987. Comparison of three sampling methods in estimating stand parameters for a tropical forest. For. Ecol. Manage. 21:119-127.

Schreuder, H. T., Gregoire, T. G., and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons, NY. 446 pp.

Scott, C.T. and Bechtold, W.A. 1995. Techniques and computations for mapping plot clusters that straddle stand boundaries. For. Sci. Monograph 31, 41:46-61.

Scott, C. T., Cassell, D. L., and Hazard, J. W. 1993. Sampling design of the U.S. National Forest Health Monitoring Program. In Nyyssonen, A., Poso, S., Rautala, J., eds. Proc. Ilvessalo Symposium on National Forest Inventories. Helsinki, Finland, August 17-21, 1993. Finnish Forest Research Inst., Res. Paper 444. Pp. 150-157.

Shao, J and Tu, D. 1995. The jackknife and bootstrap. Springer Series in Stat 516 p.

Smith, S.J. 1997. Bootstrap confidence limits for groundfish trawl survey estimates of mean abundance. Can J Fish Aquat Sci 54:616-630.

Ueng,C.Y., Gadbury, G.L. and Schreuder, H.T. 1997. Robust regression analysis of growth in basal area of natural pine stands in Georgia and Alabama, 1962-72 and 1972-82. USDA Forest Service RM Forest and Range Exp Station Res Paper RM-RP-331.

Williams, M.S. 1998. Distinguishing between change and growth in forest surveys. Can. J. For. Res 28:1099-1106.

Williams, M. S. and Schreuder, H. T. 1995. Documentation and evaluation of growth and other estimators for the mapped design used by FIA: A simulation study. For. Sci. 31, 41:26-45.

Williams, M.S. , Williams, M.T. and Mowrer, H.T. 2000. A method of correcting for off-plot influences on circular fixed-area plots in environmental surveys. Submitted to J. Agric. Biol. and Env Statistics.

Zeide, B.1992. Has pine growth declined in the Southeastern United States? Conserv. Biology 6:185-195.

RMRS
ROCKY MOUNTAIN RESEARCH STATION

The Rocky Mountain Research Station develops scientific information and technology to improve management, protection, and use of the forests and rangelands. Research is designed to meet the needs of National Forest managers, Federal and State agencies, public and private organizations, academic institutions, industry, and individuals.

Studies accelerate solutions to problems involving ecosystems, range, forests, water, recreation, fire, resource inventory, land reclamation, community sustainability, forest engineering technology, multiple use economics, wildlife and fish habitat, and forest insects and diseases. Studies are conducted cooperatively, and applications may be found worldwide.

Research Locations

Flagstaff, Arizona
Fort Collins, Colorado*
Boise, Idaho
Moscow, Idaho
Bozeman, Montana
Missoula, Montana
Lincoln, Nebraska
Reno, Nevada
Albuquerque, New Mexico
Rapid City, South Dakota
Logan, Utah
Ogden, Utah
Provo, Utah
Laramie, Wyoming

*Station Headquarters, Natural Resources Research Center,
2150 Centre Avenue, Building A, Fort Collins, CO 80526