Influence of Tree Spatial Pattern and Sample Plot Type and Size on Inventory Estimates for Leaf Area Index, Stocking, and Tree Size Parameters

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Abstract

Sampling with different plot types and sizes was simulated using tree location maps and data collected in three even-aged coast redwood (*Sequoia sempervirens*) stands selected to represent uniform, random, and clumped spatial patterns of tree locations. Fixed-radius circular plots, belt transects, and variable-radius plots were installed by simulation. Bootstrap sample means, coefficient of variation (CV), and 95 percent confidence intervals were calculated for sample estimates of eight important stand parameters. Percent CV models depicted sample precision and enable calculation of minimum sample size for forest inventories. Precision differed between stand parameters e.g., dominant height and mean top height estimates were most precise; in many cases four times as precise as density estimates. Precision was affected more by spatial pattern than plot type, and generally ranked: uniform > random >> clumped. Density, average diameter, and average height estimate precision was especially sensitive to spatial pattern, and generally poorer in variable-radius plots. However, variable-radius plots generally produced the most precise estimates of basal area, volume, and leaf area index. Quantitative descriptions of sample stand structure and spatial pattern provide a basis for comparison or application of results to other forests with similar characteristics.

Key words: bootstrap confidence intervals, coefficient of variation, precision, Ripley's K, sampling simulation, *Sequoia sempervirens*

Introduction

Forest inventory data are increasingly being used for objectives other than estimating wood product yields. Objectives include assessment of ecosystem structure and function, carbon storage and sequestration, and "ground truthing" remotely sensed data. Users of forest inventory data are often interested in a variety of parameters (e.g., stem density, stocking, leaf area index) and demand different levels of accuracy and precision of sample estimates. Factors such as forest community composition, size, and structure influence sample design when the objective is to obtain an adequate sample with minimal sampling effort. Comparing estimates of precision across a wide range of variability in tree size or spatial patterns in real stands shows how each variable affects precision. The influence of sample plot type and size, and spatial pattern of tree locations on the accuracy and precision of key stand parameter estimates has not been examined in regenerating stands of coast redwood (*Sequoia sempervirens*) in north coastal California.

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Redwood is shade tolerant and long lived. Clumping of stump sprout regeneration around cut stumps results in aggregated spatial patterns. As a consequence of these and other factors, regenerating redwood stands can have wide tree-size distributions and complex spatial arrangements of trees. Since spatial pattern is expected to affect precision of estimates obtained from sample plots (Lessard et al. 2002, Martin 1983), it may be advantageous to account for spatial pattern when sampling by altering plot size or the number of plots, or by stratifying sampling according to differences in spatial pattern. However, less is known about how much or how differently spatial pattern can affect inventory estimates for different parameters obtained from different plot types and plot sizes.

Sampling efficiency in forest types other than redwood has been examined extensively, but only for a restricted number of comparisons e.g., between plot types or stand parameters. When viewed collectively, patterns emerge from these results: Fixed-radius circular plots generally yielded the most accurate estimates of stand density and were more time-efficient than other fixed-area methods. Variable-radius plots were most time-efficient, but tended to underestimate density. Belt transects were least time-efficient (Sparks et al. 2002). Bormann (1953) tested different fixed-area plot shapes, and found that longer belt transects produced more precise estimates than shorter rectangular plots of the same area when sampling across changing contour, soil, or vegetation, and when sampling sporadic species. Lessard et al. (2002) showed that, when sampling an average of *n* trees per plot, density estimates from fixed-radius plots were more precise than estimates obtained from *n*-tree distance sampling. However, fixed-area sampling was generally more time-consuming than distance sampling methods. Kint et al. (2004) found that distance sampling was generally more efficient than plot sampling for estimation of structural indices (i.e., nearest-neighbor spatial statistics; species distribution patterns; tree-size differentiation) in forest stands. Markedly different sample sizes may be needed to achieve a specified level of accuracy or precision for different attributes or in stands with different tree sizes (Gray 2003). Sampling can be more efficient when more numerous smaller plots are installed, however below a certain plot size, estimates are prone to bias and many more plots are required to achieve a given level of precision (Lynch 2003).

The objective of our study was to examine how sample estimates for eight important stand parameters were affected by sample plot type and size, and the spatial pattern of tree locations. Inventory estimates for traditional forest stand parameters (basal area, volume, density, average tree diameter and height, and dominant height), mean top height (an alternate height metric), and leaf area index were obtained by simulating the installation of three different plot types – each having a wide range of plot sizes tested - in three redwood stands with different spatial patterns. Leaf area index (LAI) was examined because it is emerging as a key variable in forest ecosystem research and modeling (Asner et al. 2003, Berrill and O'Hara 2007) and management (O'Hara 1998). Dominant height and mean top height were examined because of their role in site index determination. Site index estimates are sensitive to measurement error, height growth prediction error, sample size, and method of calculating average height for the larger trees in the stand (Garcia 1998). Larger trees are selected based on conventions such as 'top height' or 'dominant height'. Top height is the average height of the *n* largest diameter trees per unit area. Theoretically this metric is not affected by thinning methods that target smaller trees for removal. Dominant height is the average height of dominant trees, or dominant and codominant trees, or trees above a certain proportion of the dbh distribution. It can be sensitive to changes in density when based on proportions of the dbh distribution. Sampling simulation results for these eight stand parameters were obtained in stands with similar structural characteristics but different spatial patterns (i.e., uniform, random, or clumped) to examine effects of spatial pattern on sample estimates.

Methods

Redwood-dominated stands were sampled on Jackson Demonstration State Forest (JDSF) near Ft. Bragg, Mendocino County, California. Redwood stands on JDSF regenerated naturally, occasionally supplemented by planted seedlings, after the old growth forest was progressively removed mainly by diameter-limit cutting or commercial clearcutting between 1880 and 1950. In three stands, a well-stocked area dominated by redwood was selected for measurement. A large rectangular sample block was established: (i) in a dense stand located on an upper slope (0.2 ha); (ii) in a less dense stand on a lower slope (0.5 ha), and; (iii) in a stand comprising widely-spaced clumps of redwood trees located on an alluvial flat (0.4 ha). All trees >10 cm diameter at 1.37 m breast height (dbh) were mapped, and measured for dbh, total height, and height to live crown base – defined as stem height above which the tree crown was generally continuous on one or more sides. Two breast height increment cores gave sapwood data for tree leaf area estimation. Pith-to-bark cores collected from dominant trees gave approximate breast height age of the sample stands.

Tree leaf area was predicted for each tree using tree-size and sapwood cross-sectional area data and equations presented by Berrill (2008) and Stancioiu and O'Hara (2005). Tree volume was estimated from dbh and height (Wensel and Krumland 1983). Tree data, and volume and leaf area estimates were summarized for each large rectangular sample block. The spatial pattern of tree locations in each block was characterized using the Ripley's K-function (Ripley 1981). Since a uniform pattern was not detected in any block, a low thinning was simulated in the largest block with the objective of reducing density in sprout clumps to create a more uniform pattern and concurrently reducing tree-size variability (to better align it with variability in the other two blocks).

Sampling within the three large rectangular blocks (each representing either uniform, random, or clumped patterns) was simulated for three plot types across a range of plot sizes. Circular fixed-radius plots, variable-radius plots, and fixed-width transect plot types were tested. Toroidal edge correction was applied to each large rectangular block (Haase 1995). Thirty randomly located plot centers were generated using the S-Plus Spatial Module (Insightful Corp. 2005) for sampling within each block. Trees were classified as 'inside plot' when their stem center point fell within the boundaries of fixed-area circular or transect plots or within the critical radius R_i for variable-radius sample plots. Trees inside plot boundaries were identified by calculating an inter-point distance between plot center and each tree location defined by pairs of x and y coordinates and comparing the inter-point distance against the defined plot radius or critical radius.

Circular fixed-radius plots of areas 0.005, 0.01, 0.015…0.1 ha were established at each plot center point. Randomly located plot centers defined the easting (the x of an x,y pair of location coordinates) for the centerline of north-south fixed-area belt transects running the entire length (same x, vary y approx. 50 m) of each large block. The transect width was varied to create rectangular belt transects with sample areas of 0.005, 0.01, 0.015…0.1 ha. Tree size and leaf area data for trees in each fixed-area circular and transect plot were summarized to the stand-level giving basal area (BA), volume, LAI, density, arithmetic average dbh and average height. Dominant height was calculated as average height of trees with dbh above the 75th percentile of the dbh distribution in each sample plot. Mean top height was average height of the largest 100 stems/ha in terms of dbh in each sample plot.

Variable-radius plots were established on each randomly located plot center. A range of BA factors (BAF) were applied. Basal area per hectare was obtained by multiplying the count of sample trees by the BAF. The tree factor gave the number of trees per hectare represented by each sample tree (Husch et al. 2003). Stand density was the sum of tree factors for sample trees. Volume per hectare was calculated from tree volume and the tree factor for all sample trees. Leaf area index (LAI) was calculated from tree leaf area LA_i and the tree factor TF_i for all sample trees, such that: $LAI = \sum(LA_iTF_i)/10000$. The weighted average height of trees in the upper 25 percent of the diameter distribution, weighting by the tree factor, gave dominant height. The approximate diameter distribution was obtained by replicating each sample tree dbh a total of TF_i times. Dominant trees had a dbh greater than the 75th percentile of the replicated distribution. An approximate mean top height was obtained by taking the TF_i-weighted average height of trees representing the largest 100 stems/ha.

For each plot type, re-sampling with replacement from the summary data for each plot size gave bootstrapped means, variances, and 95 percent confidence intervals for each stand parameter (Crawley 2002). To enable application of our findings in stands with different densities (having different number of trees per plot for a given plot size), results were presented in terms of average number of trees per plot instead of plot size, and bootstrap means and confidence intervals were presented as percent deviations from the population summary data for the large blocks. Results were summarized to give the minimum average number of trees per plot needed to obtain 95 percent confidence intervals for sample estimates within ±5 percent or ±10 percent deviation from the estimate. Percent deviations of the bootstrap sample means and confidence intervals from the population summary data were plotted against the average number of trees at each plot size or level of BAF, depicting sample mean estimates and precision. Coefficient of variation of the mean (CV) – the ratio of bootstrap sample standard deviation to the sample mean – was also calculated in percent terms to enable direct comparison between stands with different spatial patterns that each had different stand parameters. To facilitate interpretation and future implementation of results, percent CV (Y) was regressed against average number of trees per plot (X) for each plot type sampling each spatial pattern. Five equations were tested: Power: $Y = aX^b$ Logarithmic: $Y = a + b\ln(X)$ Exponential: $Y = ae^{bX}$ Type III exponential: $Y = ae^{b/X}$ and Schumacher: $Y = ae^{-bX^c}$ (Schumacher 1939).

Fitted models were compared in terms of goodness-of-fit (AIC) and residual bias. Percent CV predicted using the best model was plotted against average number of trees per plot for each plot type and spatial pattern, depicting differences in sample precision. Data were analyzed using S-Plus statistical analysis software (Insightful Corp. 2005).

Results

The three sample stands had relatively similar stocking in terms of BA and LAI, but different densities, average tree diameter, and total standing volume. Low thinning simulated in Block 1 removed stems ≤ 40 cm dbh, all Douglas-fir, and reduced density in redwood sprout clumps. Average tree size increased from 55 cm to 78 cm dbh. Dominant height, calculated as the average height of trees in the top 25 percent of the dbh distribution, increased from 54.4 m to 58.0 m as a result of low thinning. Mean top height, the average height of the 100 largest dbh trees per ha, was less affected by thinning. It only decreased from 56.2 m to 55.4 m. The resulting pure redwood stand had a uniform spatial pattern at scales up to 7 m. Thinning to create a uniform pattern reduced density by 65 percent and BA by 40 percent in the lower slope stand, and the range and variability of tree sizes became comparable to the stands on the upper slope and alluvial flat with random and clumped spatial patterns respectively (*table 1*).

Table 1—*Summary data for three sample blocks on Jackson Demonstration State Forest.*

Stand parameter/descriptors	Block 1[1]	Block 2	Block 3
Topography	Lower slope	Upper slope	Alluvial flat
Sample block area (ha)	0.5	0.2	0.4
Species >10 cm dbh	Redwood	Redwood	Redwood
Approximate age (years)	100	85	85
Number of trees sampled	90	230	292
Density (stems/ha)	180	1150	730
Average dbh (cm)	78.4	39.8	45.8
Standard deviation dbh (cm)	21.1	19.9	23.8
Minimum dbh (cm)	41.7	10.7	10.0
Maximum dbh (cm)	138.6	112.7	100.0
Standard deviation height (m)	7.96	10.7	13.7
Minimum height (m)	31.3	9.6	5.5
Maximum height (m)	63.8	50.1	53.3
Dominant height (m)	58.0	43.4	44.1
Mean top height (m)	55.4	44.5	45.7
Basal area (m^2/ha)	93.0	179.0	152.5
Volume (m^3/ha)	1401	1961	1684
Minimum tree leaf area (m^2)	88.7	0.5	0.3
Maximum tree leaf area (m^2)	771.7	616.8	596.6
Leaf area index (LAI m^2/m^2)	5.6	10.7	10.8
Stand density index (SDI)	442	957	758
Site Index – base age 50 yr (m)[2]	39.9	31.8	32.4
Spatial pattern[3]	Uniform	Random	Clumped
Scale of uniformity/clumping	0-7 m	-	0-12 m

[1]Data for Block 1 after simulated thinning in stand with minor Douglas-fir component, clumped spatial pattern < 7 m, 520 stems/ha, 55 cm av. dbh, 157.2 m^2/ha BA, 2223 m^3/ha volume, and LAI 9.9 m^2/m^2.
[2]Wensel and Krumland (1986).
[3]Spatial patterns described using Ripley's K with L-function transformation.

Stem maps and Ripley's K with L-function transformation depict spatial patterns in the three stands (*fig. 1*). The *L(d)* statistic for the upper-slope stand stayed within 'envelope' limits of complete spatial randomness despite the presence of a few multiple-stem clumps of redwood. Significant clumping was detected in the alluvial flat stand at scales < 12 m, while complete spatial randomness beyond 12 m suggested that widely spaced clumps were randomly distributed throughout the stand.

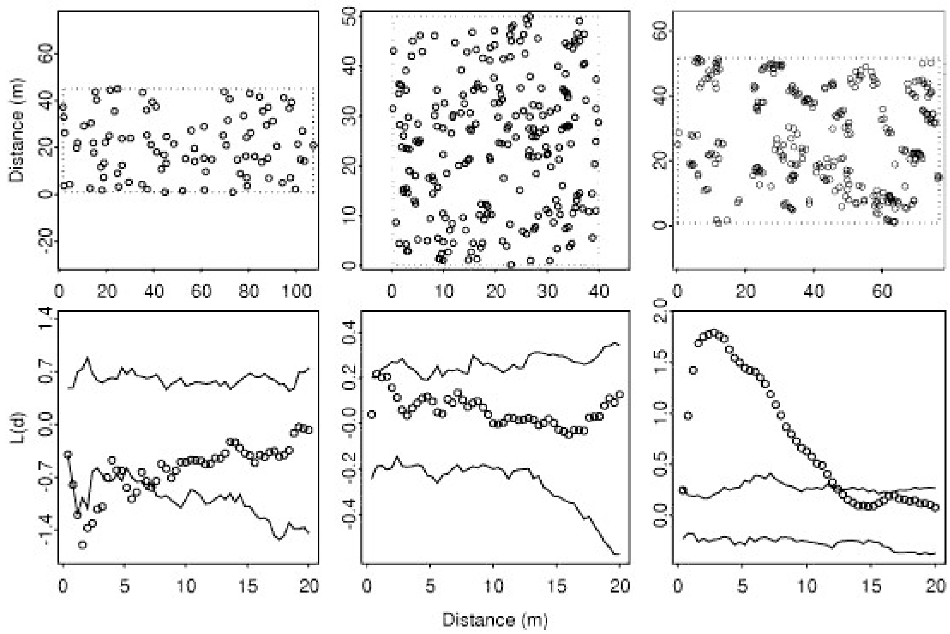

Figure 1—Stem maps and Ripley's K with L-function transformation for the lower slope (left), upper slope (center), and alluvial flat (right) stands. Circles represent tree locations in stem maps (above) and the L(d) statistic (below); lines represent upper and lower limits of complete spatial randomness. Uniform pattern indicated by L(d) falling below lower limit; clumped pattern when L(d) above upper limit.

Sample simulation results showed that sample estimates from small plots deviated from the population mean. Differences between the estimate for the large sample block and the average estimate from n = 30 randomly-located sample plots were evident when fewer than 20 trees per plot were sampled in the uniform thinned stand and when sampling fewer than 30 trees per plot in the stand with a random spatial pattern. Results indicated that some differences between population and sample estimates can be expected irrespective of plot type or number of trees per plot when using 30 randomly-located plots to sample clumped stands (*fig. 2*).

Sample variance for all stand parameters decreased as plot size increased. These increases in sample precision are depicted as 'tapering' of 95 percent confidence intervals around the bootstrap mean of sample plot estimates. However, the marginal benefit – in terms of greater precision – of expanding fixed-area plots or lowering the BAF in variable-radius plots to capture more trees generally decreased as number of trees per plot progressively increased. This effect was most pronounced when the average number of trees per plot increased beyond 30 trees for estimates of BA, volume, and LAI, and beyond 20 trees for dominant and mean top height. Results for density generally indicated that important improvements in precision were still being obtained as plots were expanded to capture around 40 trees per plot (*fig. 2*).

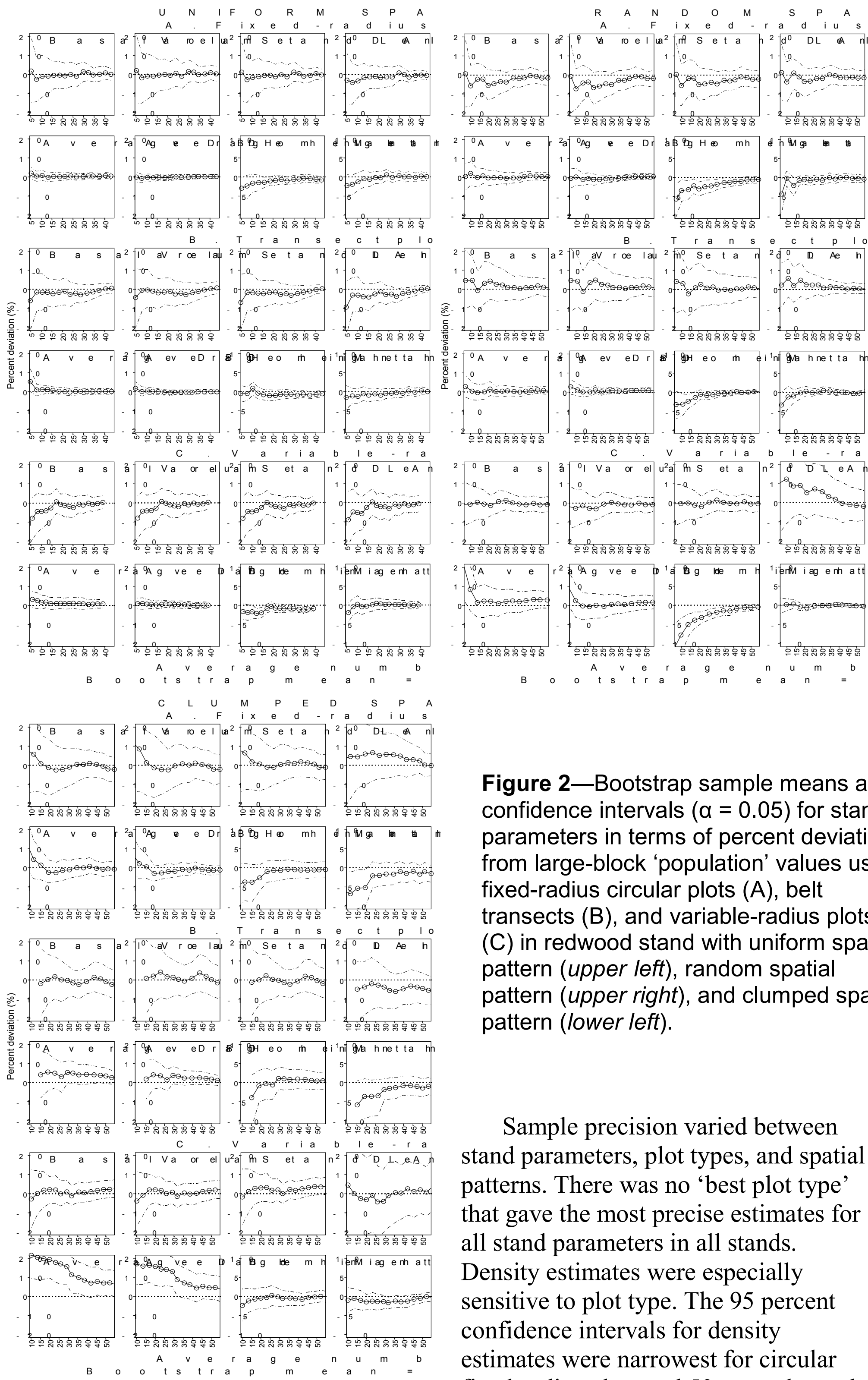

Figure 2—Bootstrap sample means and confidence intervals (α = 0.05) for stand parameters in terms of percent deviation from large-block ‘population’ values using fixed-radius circular plots (A), belt transects (B), and variable-radius plots (C) in redwood stand with uniform spatial pattern (*upper left*), random spatial pattern (*upper right*), and clumped spatial pattern (*lower left*).

Sample precision varied between stand parameters, plot types, and spatial patterns. There was no ‘best plot type’ that gave the most precise estimates for all stand parameters in all stands. Density estimates were especially sensitive to plot type. The 95 percent confidence intervals for density estimates were narrowest for circular fixed-radius plots and 50 m north-south transects. Transects gave the most precise estimates of density when an average of 30 to 40 trees per plot were sampled. Variable-radius plots generally produced more precise estimates of stand BA, volume, and LAI, especially in the clumped stand.

Plot type had little effect on precision of estimates in the uniform stand where ≤10 trees per plot were needed to obtain a 95 percent confidence interval of ±5 percent deviation from estimates of average dbh, average height, dominant height, or mean top height in all plot types (*table 2*).

Table 2—*Average number of trees per plot needed for bootstrap confidence intervals (α = 0.05) to equal ±5% or ±10% deviation from parameter estimates in stands with uniform, random, and clumped spatial patterns, sampled using fixed-radius circular plots, belt transects, and variable-radius plots. C.I. = confidence interval; LAI = leaf area index; Av. = average. Dom. = dominant; MTH = mean top height.*

Spatial pattern[1] and plot type	C.I.±10% deviation[2]				C.I.±5% deviation[2]			
	Average number of trees per plot							
	BA	Volume	LAI	Density	Av. dbh	Av. ht	Dom. ht	MTH
A. Uniform								
Circular plot	12	13	10	8	<8	<8	10	9
Belt transect	9	9	8	<8	<8	<8	<8	<8
Variable radius	8	9	8	10	<8	<8	<8	<8
B. Random								
Circular plot	11	12	12	11	13	8	12	9
Belt transect	22	22	23	12	9	<8	12	12
Variable radius	9	9	9	42	43	34	16	<8
C. Clumped								
Circular plot	30	33	30	38	40	28	35	40
Belt transect	26	29	27	31	29	18	40	40
Variable radius	15	14	15	>50	>50	>50	26	17

[1]Uniform pattern: Block 1 thinned to 180 stems/ha; random pattern: Block 2; clumped pattern : Block 3.
[2]Average difference (percent deviation) between sample estimate and upper/lower bounds of 95% (α = 0.05) confidence interval for estimates from simulated sample of n = 30 plots.

Sample estimates for the clumped stand were almost always least precise. Variable-radius plots produced much poorer estimates of density in stands with random and clumped spatial patterns. Variable-radius plots needed an average of 42 trees per plot to achieve a 95 percent confidence interval of ±10 percent deviation from density estimates in the stand with a random spatial pattern. This level of precision was not achievable sampling the clumped stand with over 50 trees per plot in 30 randomly located variable-radius plots (*fig. 2*). However, regression models depicting relationships between coefficient of variation (percent) and average number of trees per plot indicated that spatial pattern barely affected the precision - in terms of coefficient of variation – of variable-radius plot estimates of BA, volume, and LAI. Spatial pattern also had less effect on variable-radius plot dominant height and mean top height estimate precision than estimates from fixed-radius circular plots or belt transects. In general, sample precision was affected more by spatial pattern than plot type (*fig. 3*). Models describing coefficient of variation as a function of the number of trees per plot for each plot type and spatial pattern (*table 3*) had average prediction errors (RMSE) of only 1.1 percent (max. error 2.3 percent).

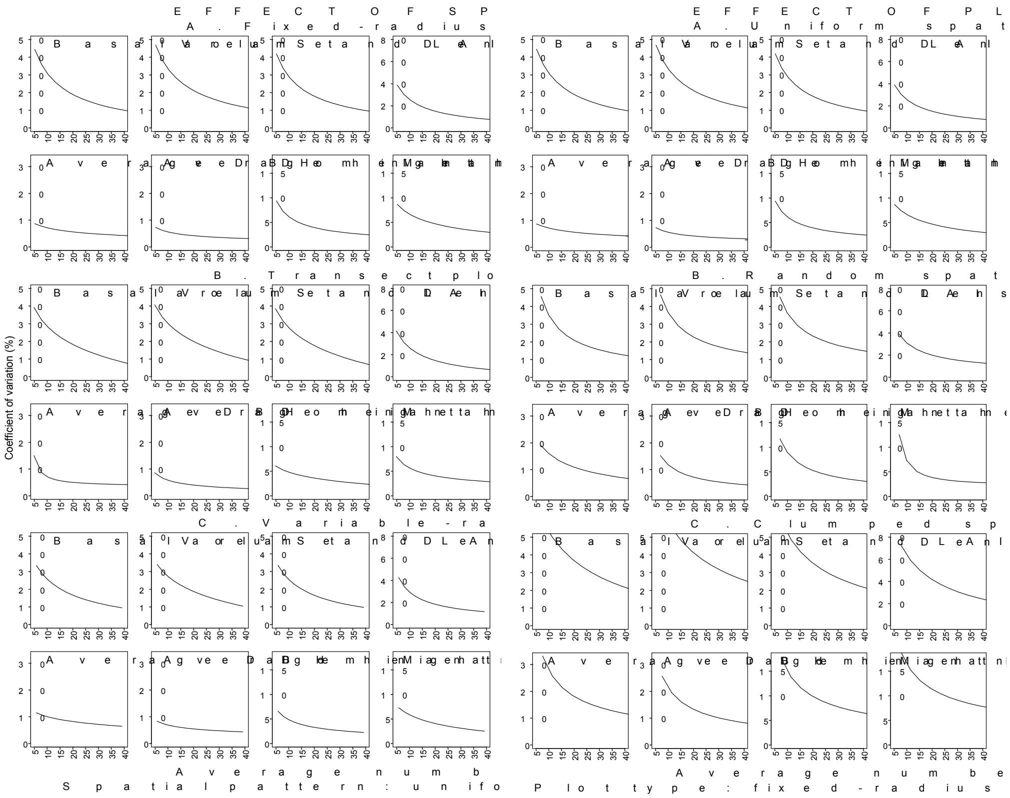

Figure 3—Effect of spatial pattern (*left*) and plot type (*right*) on coefficient of variation (percent) for sample estimates from n = 30 fixed-radius circular plots, 50-m belt transects, and variable-radius plots in stands with uniform, random, or clumped spatial patterns.

Discussion

Sample precision is affected by stand structure (e.g., Gray 2003) and spatial pattern of tree locations (e.g., Lessard et al. 2002). Confounding effects of structural differences were reduced by sampling even-aged redwood stands with similar stocking (BA, LAI). Thinning in Block 1 (the older stand) reduced tree size variability to levels comparable with the two other (younger) stands (*table 1*). Thinning had a greater impact on the estimate of dominant height than mean top height, suggesting that measures of top height are more robust metrics than dominant height for site index estimation when diameter distributions of even-aged stands are altered by low thinning. However, both top height and dominant height estimates are sensitive to plot size due to tree selection effects; estimates typically increase with increasing plot size (Garcia 1998; Magnussen 1999). Similarly, estimates from smaller plots may be more sensitive to spatial autocorrelation of tree size i.e., from microsite differences and genetics of sprouting species such as redwood. The plot size effect was evident in this study when increasing bootstrap means for dominant height and mean top height of redwood were observed with increasing plot size in most sampling simulations irrespective of plot type or spatial pattern (*fig. 2*).

Table 3—*Models of coefficient of variation (%) as a function of average number of trees per plot for eight parameter (parm.) estimates from three plot types sampling three spatial patterns.*

Parm.	SP[1]	PT[2]	F[3]	*a*	*b*	*c*	Parm.	SP[1]	PT[2]	F[3]	*a*	*b*	*c*
BA	U	F	S	164.79	0.71	0.37	*DBH*	U	F	S	31.36	0.90	0.22
	U	T	L	62.53	-14.76	-		U	T	E3	3.54	7.02	-
	U	V	S	90.41	0.47	0.43		U	V	L	16.11	-2.63	-
	R	F	P	194.33	-0.74	-		R	F	S	91.07	0.90	0.29
	R	T	L	69.94	-14.48	-		R	T	S	50.37	0.61	0.33
	R	V	P	94.09	-0.55	-		R	V	P	110.11	-0.55	-
	C	F	S	125.09	0.26	0.52		C	F	P	117.94	-0.63	-
	C	T	E3	12.47	21.04	-		C	T	P	334.59	-0.88	-
	C	V	E3	9.46	15.68	-		C	V	S	31.77	0.03	0.75
VOL	U	F	S	161.96	0.68	0.37	*HT*	U	F	P	14.43	-0.41	-
	U	T	L	63.90	-14.66	-		U	T	P	20.14	-0.54	-
	U	V	L	55.64	-12.32	-		U	V	P	15.04	-0.34	-
	R	F	P	176.34	-0.68	-		R	F	P	60.49	-0.71	-
	R	T	L	74.74	-15.67	-		R	T	P	32.53	-0.58	-
	R	V	P	85.55	-0.52	-		R	V	S	31.58	0.07	0.69
	C	F	S	162.56	0.38	0.43		C	F	P	102.23	-0.68	-
	C	T	E3	15.47	18.37	-		C	T	P	395.90	-1.00	-
	C	V	E3	10.23	14.19	-		C	V	S	27.53	0.03	0.69
LAI	U	F	S	209.91	0.96	0.32	*DHT*	U	F	P	27.27	-0.65	-
	U	T	L	61.78	-14.74	-		U	T	L	8.85	-1.75	-
	U	V	S	125.13	0.71	0.35		U	V	P	17.68	-0.56	-
	R	F	P	155.94	-0.63	-		R	F	P	50.99	-0.76	-
	R	T	L	74.57	-15.05	-		R	T	S	43.48	0.60	0.46
	R	V	S	80.76	0.49	0.36		R	V	P	147.31	-1.08	-
	C	F	S	231.58	0.69	0.33		C	F	P	59.63	-0.60	-
	C	T	E3	12.94	20.53	-		C	T	E3	3.95	22.97	-
	C	V	E3	9.10	15.71	-		C	V	P	48.45	-0.62	-
SPH	U	F	S	312.47	1.32	0.28	*MTH*	U	F	S	25.82	0.63	0.33
	U	T	S	160.80	0.72	0.40		U	T	P	17.12	-0.48	-
	U	V	P	140.84	-0.68	-		U	V	S	16.03	0.36	0.45
	R	F	P	133.72	-0.63	-		R	F	E3	2.04	12.76	-
	R	T	S	46.95	0.06	0.87		R	T	P	68.00	-0.96	-
	R	V	P	155.02	-0.46	-		R	V	S	142.08	2.28	0.19
	C	F	S	258.37	0.58	0.38		C	F	P	56.39	-0.54	-
	C	T	P	272.54	-0.64	-		C	T	E3	4.17	24.21	-
	C	V	P	329.08	-0.56	-		C	V	L	15.75	-3.16	-

[1] Spatial pattern: U = uniform; R = random; C = clumped.
[2] Plot type: F = fixed-radius circular; T = 50-m belt transect; V = variable-radius plot.
[3] Functions: P = power; L = logarithmic; E3 = type III exponential; S = Schumacher.

The marginal benefit - in terms of precision - of sampling additional trees (by increasing plot size) decreased with increasing number of trees sampled (*fig. 2, 3*). This result implied that smaller plots or higher BAF should be favored in terms of statistical efficiency. In practice, BAF are typically selected to capture around 5 to 12 trees per plot (Avery and Burkhart 1994). However, simulation results indicated that below a threshold of approximately 10 redwood trees per plot, sample variance and confidence intervals for the sample mean could increase dramatically. The effect of spatial pattern on precision of some sample estimates was greater in smaller plots (*fig. 3*). The CV models (*table 3*) can be used to define approximate minimum sample size for various forest inventory strategies. For example, a fixed-radius plot size capturing an average of 20 trees in a clumped stand is predicted to generate BA estimates with a coefficient of variation of 36.8 percent, therefore the number of plots needed to obtain an estimate within ±5 percent of the population value at the 0.80 probability level ($t_{0.2,\infty} = 1.282$) is approximately $n = ((1.282*36.8)/5)^2 \approx 89$ (Avery and Burkhart 1994). Alternatively, the number of variable-radius plots (that also capture an average of 20 trees per plot) needed to obtain BA estimates with same level of precision and confidence is approximately 28 (based on predicted CV of 20.7

percent). However, around 250 such variable-radius plots would be needed in the clumped stand to obtain density estimates within ±5 percent of the population value at the 0.80 probability level; density estimates from 28 variable-radius plots capturing an average of 20 trees per plot were predicted to be within ±15 percent of the population value at the 0.80 probability level. These examples illustrate the sensitivity of sample precision to changes in plot type and between stand parameters.

The general trend in all plot types was of decreasing precision as spatial pattern changed from uniform to random to clumped (*fig. 3*). These findings are consistent with results presented by Lessard et al. (2002) showing that the expected variance of estimates from a Poisson-distributed random spatial pattern will always be less than estimates from a negative binomial-distributed approximation of a clumped pattern of tree locations. However, our results indicated that the effect of spatial pattern differed markedly between some stand parameters and its effects can interact with plot type. For example, spatial pattern most affected precision of redwood density estimates from variable-radius plots and precision of average dbh and height estimates in all plot types. Precision of BA, volume, and LAI in variable-radius plots capturing >15 trees was least affected by spatial pattern. Variable-radius plots generally made more precise estimates of 'total' stand parameters such as BA, volume and LAI where larger trees make a greater contribution towards the estimate. Average dbh and height estimate precision was poorest in variable-radius plots, except in smaller plots within the clumped stand where fixed-area plots performed poorly. Variable-radius plots consistently produced the least precise estimates of density for a given sample size. This problem was most pronounced in the stands with random or clumped spatial patterns (*fig. 3*). Hebert et al. (1988) and Schreuder et al. (1987) also found variable-radius plots to make marginally more precise estimates of BA, but less precise estimates of density when compared with fixed-radius plots. Schreuder et al. (1987) found fixed-area sampling most efficient for stand density and number of small trees, and variable-radius sampling best for density in larger dbh classes. In differentiated stands or multiaged stands with numerous small trees and fewer large trees, fixed-area plots or transects can capture more small trees and fewer large trees than are needed. This problem can be mitigated by installing a series of concentric plots each sampling a different size class or stand component i.e., cohort or canopy layer (Spurr 1952), by implementing a multistage design (Thompson 2002), or by using variable-radius plots.

The accuracy and precision of estimates can be affected by sampling and non-sampling error. Sampling errors arise because only part of the population of interest was sampled. They tend to decrease with increasing sample size, and can only be avoided by complete enumeration (Avery and Burkhart 1994). Non-sampling errors include measurement errors and incorrect sample plot establishment. These errors tend to have a greater impact in smaller plots, and persist with increasing sample size (Thompson 2002). Belt transects have a greater proportion of edge, and therefore a greater probability of sampling bias from incorrect plot establishment when 'borderline' trees are present (Bormann 1953). Variable-radius plots are susceptible to systematic errors caused by incorrect calibration, hidden or leaning trees, and errors in slope correction (Avery and Burkhart 1994). Another potential non-sampling error is bias introduced by inappropriate volume tables or allometric equations (Chave et al. 2004). Our analysis ignores the uncertainty and propagation of errors associated with predictions of redwood tree volume and leaf area and therefore underestimates the uncertainty around these estimates.

Sampling simulations were conducted using data collected in 85 to 100 year old redwood stands where density and tree size variability remained high despite many decades of competition. The range of spatial patterns and tree sizes should encompass conditions found in many size-differentiated natural stands of redwood. Stand attributes have been quantified using detailed stand summary data (*table 1*) and Ripley's K analysis (*fig. 1*), giving three-dimensional characterizations of sample stand structure. Application of results in stands with different densities or tree sizes is facilitated because we reported coefficient of variation and confidence intervals in percentage terms, and average number of trees per plot instead of plot size. Narrower confidence intervals around sample estimates can be expected in stands with greater uniformity of tree size or spatial pattern, such as younger stands and plantations.

Conclusion

Redwood forest managers and researchers interested in precise density estimates (e.g., to design and evaluate silvicultural treatments, monitor changes during stand development, or for spacing experiments), should favor fixed-area plots over variable-radius plots in stands with random or clumped tree spacing. Variable-radius plots were advantageous when sampling BA, volume, and LAI. Choice of plot type hardly affected precision of dominant and mean top height estimates, except in the clumped stand where estimates from variable-radius plots were more precise. In general, larger plots will be needed to achieve a desired level of precision when sampling stands with a higher degree of clumping. Larger plots are less likely to underestimate dominant height or top height. Top height was less affected by thinning and is recommended over dominant height in managed stands. Sampling in redwood forests should be preceded by careful definition of objectives and consideration of stand structure and spatial pattern before making decisions about plot type and sample size.

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