Application of Mapped Plots for Single-Owner Forest Surveys

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ABSTRACT

Mapped plots are used for the national forest inventory conducted by the US Forest Service. Mapped plots are also useful for single ownership inventories. Mapped plots can handle boundary overlap and can provide less variable estimates for specified forest conditions. Mapping is a good fit for fixed plot inventories where the fixed area plot is used for both mapping and tree sampling. However, mapping can be done with a colocated fixed area plot even though the tree inventory uses variable plots. In fact, the tree measurement plots can be completely decoupled from the plots used for measuring condition proportions, although this is not recommended.

Keywords: boundary overlap, horizontal point samples

The mapping of conditions that divide field observation plots stemmed from the same practice that was used historically on agricultural experimental plots. The practice was introduced at the national scale in the United States by the Forest Health Monitoring program and later adopted by the Forest Inventory and Analysis (FIA) program of the US Forest Service. Fixed area plots that include more than one condition are mapped so the plot measurements can be allocated to conditions. Conditions are defined by characteristics such as ownership, forest type, stand age, tree size, and density.

Plot mapping is the successor to the past FIA method of rotating plots so they only contained single conditions. Plot rotation led to a small bias in the estimates (Birdsey 1995) and is no longer considered an acceptable practice. The mapped plot design (Bechtold and Patterson 2005) was recommended (Hahn et al. 1995) as an alternative to rotating straddler plots.

FIA uses a very detailed procedure for mapping condition boundaries (Scott et al. 1995), but condition mapping can be implemented in a number of ways. For example, a grid of points could be located within the plot and the condition proportions determined by counting the grid points that fall into each condition. We show that the concept of mapping is extremely flexible and can be useful for smaller forest inventories and for inventories that use horizontal point samples (variable plots) to select sample trees. A simulation is presented to show the value of accurate plot mapping. An example application is provided to clarify the computational requirements.

Colocated Plots for Tree and Condition Samples

The mapping concept becomes very flexible if sampling for condition proportions is decoupled from sampling for tree variables. Consider the option of estimating condition proportions with a plot that is colocated with the forest inventory plot. Call these COND plots and TREE plots. Only fixed area plots will be considered here for COND plots, but TREE plots could be fixed or variable plots.

Plot mapping is the process of estimating or measuring the proportion of each plot that is in a particular forest condition. The purpose is to use the condition proportion to adjust the TREE plot condition measurements to reduce variance. The following model shows how these measurements are assumed to be related to the underlying per hectare condition mean, μ_c,

$$y_{ic} = a_{ic}\mu_c + \varepsilon_{ic}, \qquad (1)$$

where y_{ic} is the measurement of the variable of interest at TREE plot i for condition c, a_{ic} is the estimate of the proportion that is in condition c made on the colocated COND plot, and ε_{ic} is a random error term. Assume that y_{ic} has been adjusted to represent a per-acre or per-hectare value. For example, the actual plot measurement would be multiplied by 10 for one-tenth hectare fixed-area plots.

Mapped Plot Assumptions

Mapping can be advantageous, because a plot will often overlap multiple conditions. Mapped plots should provide less variable

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estimates of quantities, such as per acre volume, within conditions of interest. If the plot is half natural pine and half plantation pine, it is clear that the combined plot data are not representative of either condition.

The most important mapped plot assumption made explicit in Equation 1 is that the expected amount of y on a partial plot is proportional to a. In particular, if half the plot is in condition c, then we expect y to be half of the value for a plot fully in the condition. This is analogous to assuming that 10 ha of pine will have half the volume of 20 ha of pine. It is an assumption that is implicitly made in most forest inventories.

The a value in Equation 1 comes from the colocated COND plot. The following equation states that the expected value of a is equal to the overall condition proportion:

$$a_{ic} = A_c + v_{ic}, \quad (2)$$

where a_{ic} is the proportion of plot i in condition c, A_c is the true proportion of condition c for the area being inventoried, and v_{ic} is a random error term.

Equations 1 and 2 can be combined to get

$$\bar{y}_c = A_c \mu_c + \bar{\varepsilon}_c, \quad (3)$$

where $\bar{y}_c$ is the mean of the condition c TREE plot y values and $\bar{\varepsilon}_c$ is a random error. From Equation 3 a possible estimator for μ_c follows immediately,

$$\hat{\mu}_c = \bar{y}_c / \bar{A}_c, \quad (4)$$

where $\bar{A}_c$ is the mean of the a values from COND plots containing condition c. The mapped plot condition mean estimator given by Equation 4 is identical to what FIA uses (Bechtold and Patterson 2005) and is derived by alternative means elsewhere (Van Deusen 2004).

Condition proportions also have value for adjusting area estimates using weighted estimators. This requires each plot to be assigned a weight or expansion factor that indicates how much area the plot represents. Detailed explanation of the weighted approach is available elsewhere (Van Deusen 2007). A limited demonstration of the value of mapped plots for area estimation is given as part of the example application.

Variance Estimation

The mapped plot estimator (Equation 4) of condition means does not require TREE and COND plots to be colocated. Technically, $\bar{A}_c$ and $\bar{A}_c$ could come from independent TREE and COND plots. However, there would often be logistical advantages to computing these values at the same locations, and the correlation between TREE and COND plot measurements will reduce the variance of the mapped plot estimate. If the survey is using fixed area TREE plots, then it would make sense to use the same plot for the COND plot. On the other hand, it is conceivable that better condition proportion estimates could be made from plots measured on aerial photos. The unbiased estimator of μ_c given by Equation 4 is the same regardless of colocation, but the variance estimator will be affected.

Colocated COND and TREE Plots

The variance estimator for colocated plots is shown and demonstrated in the example application section (Equation 7). This mapped plot variance estimator (Equation 7) is given by Van Deusen (2004) and is very similar to Equation 2.46 from Cochran (1977) for estimating a ratio of means variance.

Independent COND and TREE Plots

If the COND plot is not colocated with the TREE plot, then we assume that there is no correlation between a_{ic} and y_{ic} in Equation 1. In this case, Equation 7 is not appropriate. The following variance estimator is suggested when TREE and COND plots are independent:

$$s_d^2(\hat{\mu}_c) = \frac{\bar{y}_c^2}{\bar{A}_c^4} \mathrm{Var}(\bar{A}_c) + \frac{1}{\bar{A}_c^2} \mathrm{Var}(\bar{y}_c), \quad (5)$$

where $\mathrm{Var}(\bar{A}_c)$ and $\mathrm{Var}(\bar{y}_c)$ are estimated from the measurements on the COND and TREE plots, respectively. Note that $\bar{y}_c$ is the mean of the plot condition measurements without adjustment for condition proportions. The delta method (Bishop et al. 1975, Oehlert 1992) was used to derive Equation 5.

Application to Simulated Data

A simulation is conducted to gain insight into the benefit of obtaining accurate condition proportions and colocating COND and TREE plots. This involves comparison of increasing levels of mapping precision. The effect of mapping precision is also evaluated for different levels of diversity. Diversity, for this simulation, is measured by the proportion of plots that are mapped into more than one condition.

A Y variable is generated from a normal distribution with a mean of 2,000 and a coefficient of variation of 2.5%. Plots are simulated to correspond to different levels of mapping diversity. A diversity coefficient of 0.8 means that 80% of the plots are fully in the condition and the other 20% are mapped. This level of diversity is similar to what FIA actually encounters in many southern states. The simulation is run for three diversity coefficients, 0.5, 0.7, and 0.8.

Condition mapping precision is simulated by putting the condition proportions into bins. The number of bins corresponds to the degree of rounding. Precision level 1 has 2 bins where the condition proportions are set to either 0 or 1. Precision level 2 creates 3 bins, 0, 0.5, or 1. Precision level 3 has 4 bins, 0, 0.33, 0.66, and 1. Precision level 4 has 5 bins, 0, 0.25, 0.5, 0.75, and 1. In general, precision level L has $L + 1$ bins. Each true condition proportion is assigned to the closest bin.

The simulations are repeated 10,000 times and 1,000 samples are drawn for each repetition. The simulations are performed with dependent Y and A values to simulate colocated TREE and COND plots. Identical simulations are also performed with independent A values to simulate independent TREE and COND plots, where the A values represent condition proportions.

Table 1. Simulated results with 80% of the plots fully in the condition and colocated TREE and COND plots.

Precision	$\hat{\mu}$	$\bar{A}$	$s(\hat{\mu})$	$\sigma(\hat{\mu})$
1	1,999.96	0.90	9.21	9.24
2	2,000.01	0.90	4.82	4.81
3	1,999.99	0.90	3.44	3.46
4	1,999.99	0.90	2.80	2.76
5	1,999.99	0.90	2.44	2.44
6	2,000.02	0.90	2.23	2.24
7	2,000.04	0.90	2.09	2.11
8	2,000.01	0.90	1.99	1.99
9	2,000.00	0.90	1.92	1.90
10	2,000.01	0.90	1.87	1.88
20	2,000.02	0.90	1.70	1.71
100	2,000.00	0.90	1.64	1.65
1000	1,999.99	0.90	1.63	1.64

Precision indicates the accuracy of the plot mapping with decreasing levels of rounding. The mean mapped plot estimate is $\hat{\mu}$, the mean condition proportion estimate is $\bar{A}$, $s(\hat{\mu})$ gives the mean standard error from Equation 7 and the true standard error computed from the simulation is $\sigma(\hat{\mu})$

Colocated TREE and COND Plots

The simulation results are shown in detail for diversity level 0.8 (Table 1). A range of precision levels is given along with simulation averages for $\hat{\mu}$ and $s(\hat{\mu})$ from Equation 7. The simulation average of $\bar{A}$ is what it should be (unbiased) for a diversity coefficient of 0.8, even for the low precision levels. The average of $\hat{\mu}$ is very close to the true simulation mean of 2,000, which shows that plot mapping results in unbiased estimates. The true simulation variance in column $\sigma(\hat{\mu})$ is very close to the average value in column $s(\hat{\mu})$. This shows that Equation 7 performs well.

The table provides some important insight into the effect of increasing mapping precision. Consider precision level 4 versus precision level 10. The relative decrease in confidence interval width of going from mapping into quarters versus mapping into tenths at this level of diversity is $1 - 1.88/2.76 = 0.32$, based on the true variance column ($\sigma(\hat{\mu})$). However the reduction in confidence interval width by mapping to the nearest hundredth versus tenths is $1 - 1.65/1.88 = 0.12$. Getting a 32% reduction in confidence interval width might make it worth going from mapping into quarters to mapping into the nearest tenth. The 12% reduction derived by going from tenths to hundredths might not be worth the effort. Furthermore, it may be unrealistic to think that mapping can be done to the nearest percent in the field. Going to twentieths would certainly be adequate and might be a practical compromise.

The simulation was run at diversity levels of 50, 70, and 80%. The results for the true standard error are given (Table 2) for each precision level for easy comparison. This shows that the relative improvement due to increased mapping precision is greater with greater levels of diversity. Not surprisingly, this says that surveys with a larger percentage of mapped plots will gain more by doing the mapping more precisely. The 50% diversity level shows a reduction in confidence interval width of $1 - 1.72/2.44 = 0.30$ by increasing mapping precision from tenths to hundredths. A 30% reduction in confidence interval width might be worth the extra effort. However, going to twentieths would seem to be adequate for any level of forest diversity.

Independent TREE and COND Plots

The simulation is rerun with all else being identical except an independent set of condition proportions are used to evaluate $\bar{A}$. Results are shown in detail for diversity level 0.8 (Table 3). In general, this shows that $\hat{\mu}$ remains unbiased, but its variance is considerably larger than it was for colocated COND plots. The true simulation variance in column $\sigma(\hat{\mu})$ is very close to the average value in column $s_d(\hat{\mu})$, meaning that Equation 5 performs well. Evidently, mapping precision has little effect on the variance with decoupled COND plots as long as the overall condition proportion estimate, $\bar{A}$, is unbiased. This suggests that mapping to the nearest quarter of a plot (precision level 4) is sufficient with independent COND plots at this diversity level.

The independent COND plot simulation was also run at diversity levels of 50, 70, and 80%. The true simulation standard errors are given (Table 4) for each level. This continues to show that mapping precisely is more important at higher levels of diversity. However, mapping to the nearest tenth seems more than adequate for independent COND plots.

Table 2. Summary for three levels of mapping diversity (50, 70, and 80%) with colocated TREE and COND plots.

Precision	$\sigma(\hat{\mu})$, 50%	$\sigma(\hat{\mu})$, 70%	$\sigma(\hat{\mu})$, 80%
1	17.40	11.84	9.24
2	8.81	6.10	4.81
3	6.08	4.26	3.46
4	4.66	3.36	2.78
5	3.90	2.89	2.44
6	3.36	2.57	2.24
7	3.00	2.37	2.11
8	2.77	2.23	1.99
9	2.55	2.12	1.90
10	2.44	2.05	1.87
20	1.94	1.78	1.71
100	1.72	1.69	1.63
1000	1.71	1.67	1.64

The simulation variance, $\sigma(\hat{\mu})$, is given by level of mapping precision and diversity.

Table 3. Results with 0.8 fully in the condition with independent TREE and COND plots.

Precision	$\hat{\mu}$	$\bar{A}$	$s_d(\hat{\mu})$	$\sigma(\hat{\mu})$
1	2,000.40	0.90	26.97	26.80
2	2,000.33	0.90	24.58	24.59
3	2,000.35	0.90	24.11	24.18
4	1,999.73	0.90	23.94	23.86
5	2,000.19	0.90	23.86	24.18
6	1,999.99	0.90	23.80	23.74
7	2,000.28	0.90	23.80	23.77
8	2,000.05	0.90	23.77	23.88
9	1,999.85	0.90	23.75	23.92
10	2,000.49	0.90	23.75	23.60
20	1,999.95	0.90	23.73	23.57
100	2,000.02	0.90	23.75	23.70
1000	1,999.97	0.90	23.71	23.91

The $\hat{\mu}$, $\bar{A}$ and $\sigma(\hat{\mu})$ columns are defined as for Table 1, $s(\hat{\mu})$gives the mean standard error from Equation 5.

Mapping with Variable Plots

Variable plots are not well suited to measuring condition proportions. Variable plot tree inventories should use colocated fixed area circular plots for measuring condition proportions. The fact that the TREE and COND plots are colocated will result in variance reduction. The radius of the COND plot should be compatible with the limiting tree distances determined by the basal area factor. Our suggestion is to set the radius of each COND plot equal to the limiting distance of the largest "in" tree on the TREE plot. This will ensure that at each location every condition with at least one tree will have a nonzero condition proportion.

The largest-tree limiting-distance (LTLD) method causes the COND plot radius to vary from one location to the next. This would be problematic if the LTLD mechanism for varying the COND plot radius was dependent on the condition proportions at the location. It is possible that the largest trees are always associated with a particular condition, but it is unlikely the largest tree on the plot would be correlated with the condition proportions at that location.

There is no technical reason why the COND plot needs to be large enough to encompass all the trees on the TREE plot. However, it would be illogical to assign a tree to a condition that does not exist on the colocated COND plot.

Boundary Overlap

Plot mapping also has potential for eliminating bias from property boundary overlap. The boundary overlap problem is caused by trees near the property line having a smaller selection probability than interior trees. Methods have been suggested to correct for this bias (Ducey et al. 2004, Gregoire 1982), but they require the field crew to learn specialized procedures for trees near the boundary. Furthermore, these procedures vary for trees near property corners.

Table 4. Summary for three levels of diversity (50, 70, and 80%) with independent TREE and COND plots.

Precision	$\sigma(\hat{\mu})$, 50%	$\sigma(\hat{\mu})$, 70%	$\sigma(\hat{\mu})$, 80%
1	45.81	33.84	26.80
2	40.30	30.08	24.59
3	39.53	29.82	24.18
4	38.99	29.69	23.86
5	38.88	29.64	24.18
6	39.22	29.31	23.74
7	38.95	29.14	23.77
8	38.33	29.40	23.88
9	38.28	29.53	23.92
10	38.67	29.27	23.60
20	38.49	29.16	23.57
100	38.80	29.28	23.70
1,000	38.84	29.29	23.91

The simulation variance, $\sigma(\hat{\mu})$, is given by level of mapping precision and diversity.

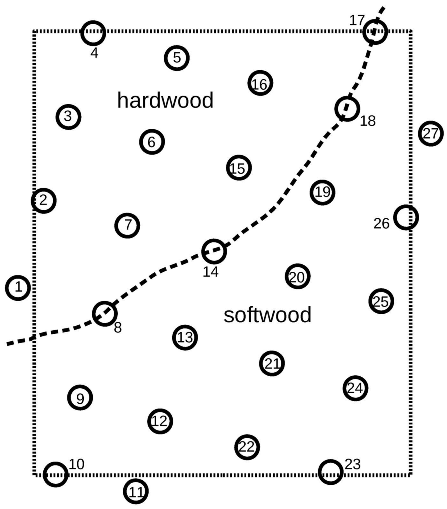

Figure 1. A depiction of a rectangular forest property with hardwood and softwood conditions. There are 27 inventory plots. Plots 4, 17, 26, 23, and 10 straddle the property boundary. Plots 1, 11, and 27 are completely outside the property. Plots 8, 14, 18, and 17 straddle the forest condition boundary.

The plot mapping solution to boundary overlap requires there to be a buffer surrounding the property where TREE plot centers have the same chance of occurring as they do within the actual property boundaries. The buffer needs to be wide enough to ensure that boundary trees have the same selection probability as trees in the center of the area of interest. For example, with circular TREE plots the buffer width should be at least equal to the plot radius. For variable TREE plots, the buffer width should be at least equal to the limiting distance of the largest tree on the property. No harm is done if the boundary is too wide, but a bias can occur if it is too narrow.

The section of a plot that lies outside the property boundary is treated as a nonforest condition. The section of the plot that is on the actual property is mapped and the on-property trees are measured. The only reason to enter the boundary zone is to provide a reference point from which to establish the plot section that overlaps the property. This results in a very simple solution to boundary overlap bias from a field crew perspective. No special field crew procedures are required. The shape of the boundary is also irrelevant with this method.

Example Application

A simple example (Figure 1) is presented to show the data and calculations that are required for a small inventory. This example includes 27 plots located on a grid oriented randomly over the property. There are hardwood and softwood forest conditions separated by a dashed line. Some of the plots straddle the condition boundary and others straddle the property boundary. A few of the plots fall completely outside the property. It might sometimes be necessary to have the field crew visit plots to make sure they do not overlap the property boundary. The assumption is that the plot mapping is done on colocated fixed area COND plots. The TREE plots could be fixed or variable.

The data for the simple inventory depicted in Figure 1 consists of (Table 5) plot condition proportions for hardwood, softwood, and nonforest conditions a_h, a_s, and a_{nf}. Each plot also has per acre cubic foot volumes for hardwood and softwood (y_h and y_s). The plot volumes are derived in the usual way. For example, if these are tenth acre plots, then each individual tree volume is multiplied by 10 so it represents a per acre value.

Estimates of per acre mean volume are obtained from the formula,

$$\hat{\mu}_c = \frac{\sum_{i=1}^{n} y_{ic}}{\sum_{i=1}^{n} a_{ic}}. \qquad (6)$$

According to Equation 6, the per acre volume estimate for the hardwood condition is obtained by dividing the sum of the y_h column by the sum of the a_h column (Table 5). The softwood estimate is obtained by summing and dividing the appropriate softwood volume and condition proportion columns. This results in the following per acre volume estimates: $\hat{\mu}_h = 1251.4$ and $\hat{\mu}_s = 1507.5$. Notice that Equation 6 is merely a reformulation of Equation 4.

Confidence intervals on the estimates from Equation 6 are obtained with variance estimates from this equation (Van Deusen 2004),

$$s^2(\hat{\mu}_c) = \frac{\hat{\sigma}_c^2}{\sum_{i=1}^{n} a_{ic}}, \qquad (7)$$

where

$$\hat{\sigma}_c^2 = \frac{\sum_{i=1}^{n} e_{ic}^2}{\sum_{i=1}^{n} a_{ic} - 1} \qquad (8)$$

and

$$e_{ic} = y_{ic} - a_{ic}\hat{\mu}_c. \qquad (9)$$

The computations required to estimate $\hat{\sigma}_c^2$ involve summing the e_{ic}^2 terms defined in Equation 9. Computation of the e_{ic} values uses the mean estimate from Equation 6.

Table 5. Data for the mapped plot inventory depicted in Figure 1.

Plot	a_h	a_s	a_{nf}	y_h	y_s
1	0.00	0.00	1.00	0	0
2	0.95	0.00	0.05	1,200	0
3	1.00	0.00	0.00	1,350	0
4	0.60	0.00	0.40	800	0
5	1.00	0.00	0.00	1,250	0
6	1.00	0.00	0.00	1,300	0
7	1.00	0.00	0.00	1,400	0
8	0.40	0.60	0.00	600	800
9	0.00	1.00	0.00	0	1,500
10	0.00	0.50	0.50	0	650
11	0.00	0.00	1.00	0	0
12	0.00	1.00	0.00	0	1,400
13	0.00	1.00	0.00	0	1,700
14	0.40	0.60	0.00	400	600
15	1.00	0.00	0.00	1,000	0
16	1.00	0.00	0.00	1,350	0
17	0.20	0.30	0.50	250	400
18	0.40	0.60	0.00	300	800
19	0.00	1.00	0.00	0	1,800
20	0.00	1.00	0.00	0	1,200
21	0.00	1.00	0.00	0	1,900
22	0.00	1.00	0.00	0	1,100
23	0.00	0.80	0.20	0	1,150
24	0.00	1.00	0.00	0	1,500
25	0.00	1.00	0.00	0	1,800
26	0.00	0.90	0.10	0	1,750
27	0.00	0.00	1.00	0	0

The proportion of each plot in the hardwood, softwood, and nonforest condition is a_h, a_s, and a_{nf}. The per acre cubic foot volume on each plot in the hardwood and softwood conditions is y_h and y_s.

Applying Equation 7 to the hardwood and softwood columns (Table 5) and taking the square root gives the following standard error estimates for hardwoods and softwoods: $\mathrm{SE}_h = 48.9$ and $\mathrm{SE}_s = 75.0$.

Approximate 95% confidence intervals on the softwood and hardwood mean volumes are $\mathrm{CI}_h = 1251.4 \pm 2 * 48.9$ and $\mathrm{CI}_s = 1507.5 \pm 2 * 75.0$. We have not included a finite population correction (FPC) factor to reduce the variance estimate (Cochran 1977) in Equation 7 for situations where a large proportion of the forest area is being sampled. Forest inventories that sample less than 10% of the forest area can safely ignore the FPC.

The mapped plot condition proportions can also be used to estimate the area in the hardwood and softwood conditions. The plot locations for this example are located on a grid. This allows for computing forest area by following standard dot grid area estimation procedures. However, we will assume that the total acreage of the property is known to be T and adjust this with the condition proportions.

First, compute the sum of all forest conditions by summing the a_h and a_s columns

(Table 5). Then, compute the proportion of this sum that is in the hardwood and softwood conditions to get: $P_h = 0.4$ and $P_s = 0.6$. The estimated area in each forest condition is then $T_h = P_h * T$ and $T_s = P_s * T$. The estimate of total volume in each condition is obtained by multiplying these area estimates by the mean per acre volume estimates obtained previously.

Finally, standard errors on total volume estimates are obtained by multiplying the per acre standard errors for hardwood and softwood by T_h and T_s. The approximate 95% confidence intervals on total volume for this example would then be $CI_h = T_h * 1251.4 \pm T_h \times 2 \times 48.9$ and $CI_s = T_s \times 1507.5 \pm T_s \times 2 \times 75.0$. No attempt is made to account for the uncertainty in the hardwood and softwood area estimates.

Was Mapping Worth the Effort?

There needs to be a demonstrable benefit before an organization adopts a new method. Mapping plots in the field and using different computational methods takes time and resources. We now show with the example data that mapping noticeably reduced the variance of the estimates. It is up to the user to decide if this variance reduction was worth the effort.

Table 6 shows three versions of mean per acre estimates for softwood and hardwood based on the example data. The first column (Mapping All) gives the results based on mapped plot estimators for all plots as discussed previously. The second column (Mapping Forest) gives mapped plot estimates for the 18 plots that are entirely forested and do not overlap the property boundary. The third column (No Mapping Forest) gives results that ignore the mapping for the 18 entirely forested plots. The property boundary overlap plots were eliminated to avoid confounding the comparison between mapping and not mapping. The No Mapping Forest column is giving conditional means and standard errors in the sense that plots with no hardwood (softwood) do not contribute to the hardwood (softwood) estimates.

Table 6 shows that the estimated means based on mapping for the Mapping All and Mapping Forest columns are very similar. As expected, the standard error is somewhat larger for the Mapping Forest column because the property boundary overlap plots are eliminated. The No Mapping Forest column means are smaller and the standard errors are much larger than those in Mapping-Forest.

Table 6. Mean and standard errors (in parentheses) for the example data.

	Mapping all	Mapping forest	No mapping forest
Hardwood	1,251.4 (48.9)	1,243.1 (61.5)	994.4 (147.5)
Softwood	1,507.5 (75)	1,490.7 (84.3)	1,341.7 (127)

Mapping all gives mapped plot results for all plots, mapping forest gives mapped plot results for the 18 plots that do not overlap the property boundary, no mapping forest gives results for the 18 nonoverlap plots with mapping ignored.

The No Mapping Forest means should be smaller, because some of the plots were only partially hardwood or softwood. Likewise, the standard errors should increase because no adjustment is made for the partial plots. Therefore, mapping can provide more precise per acre estimates for well-defined forest conditions, as the simulations suggested.

Conclusions

The potential uses of plot mapping are greatly expanded by the simple idea that the plots for measuring tree variables and the plots for measuring condition proportions do not have to be the same. The simulations and the example application make it clear that colocating the TREE and COND plots pays off in terms of variance reduction. However, unbiased estimates of condition means can be obtained even if the TREE and COND plots are not colocated.

Plot mapping is a useful technique for large- and small-scale forest inventories. Correlation between condition proportions and tree measurements made on colocated plots can result in significant variance reduction. However, condition proportions do not have to be mapped to the nearest percent. Significant variance reduction can be obtained by classifying 10 points in a dot grid fashion at each COND plot. Condition proportions obtained from an independent source or inventory can still be used to eliminate bias in forest condition estimates, but they will result in little variance reduction.

Logically, any condition that has a tree should also have a nonzero condition proportion. If not, perhaps the tree's condition should be reassigned. It could be a waste of time to define conditions that will rarely be sampled. A small inventory might only be able to support a few conditions, such as nonforest, hardwood, and softwood. Larger inventories might call each major forest type a condition. No real harm is done by keeping track of rare conditions, other than wasting field crew time, but they may need to be combined with related conditions for analysis purposes. FIA also requires that a condition be at least 1 ac in size (Bechtold and Patterson 2005) at the plot location or it is not recorded. Our results from the example application and the simulations for fixed area plots should be directly applicable to the FIA fixed plot design, even though FIA uses a configuration of four fixed area subplots.

It should be acknowledged that there are situations where plot mapping may be of little value. For example, total volume by species is available with or without mapping. Mapping is beneficial when information is required on particular forest conditions that will be encountered as the inventory proceeds. Riparian zones provide a good example. Riparian zones tend to be narrow and will frequently be overlapped by plots that also overlap the adjacent condition. Plot mapping will provide improved estimates for these special forest conditions.

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