

# The Power of FIA Phase 3 Crown-Indicator Variables to Detect Change

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**ABSTRACT:** *The goal of Phase 3 Detection Monitoring as implemented by the Forest Inventory and Analysis Program is to identify forest ecosystems where conditions might be deteriorating in subtle ways over large areas. At the relatively sparse sampling intensity of the Phase 3 plot network, a rough measure of success for the forest health indicators developed for this purpose is the ability to detect meaningful change when indicator data are pooled across two or three States. The statistical power of a test is the probability of detecting a difference of a certain magnitude when it indeed exists, and is defined as 1 minus the type II error (i.e., 1-beta). This study applies statistical power analysis to Phase 3 Crown-Indicator variables (crown density, foliage transparency, and crown dieback) to determine how many plots are necessary to detect various degrees of change at various levels of statistical power.*

**KEYWORDS:** Statistical power analysis, forest health indicators, tree crown condition, tree crown health, tree health indicators, tree crown measurement

## Introduction

The conceptual approach to forest health monitoring in the U.S. includes a component to detect long-term regional changes (Detection Monitoring), a component for assessing the practical importance and impact of observed changes (Evaluation Monitoring), and a component for conducting process-level research of cases that remain unresolved (Intensive Site Monitoring). The goal of Detection Monitoring is to identify forest ecosystems where conditions might be deteriorating in subtle ways over large areas (Riitters and Tkacz 2004). The Forest Inventory and Analysis (FIA) Phase 3 sampling frame (Bechtold and Patterson 2005) contributes to this goal by systematically sampling a set of forest health indicators over space and time. Core tables used in FIA reports (e.g., Turner and

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others 2008) document the status and trends associated with these indicators, and analysts look for signals that suggest potential problems.

Most of the indicators currently implemented on FIA Phase 3 plots were developed by the Forest Health Monitoring (FHM) Program in collaboration with the U.S. Environmental Protection Agency (Alexander and Palmer 1999). One of the original goals for indicator development was to provide statistically unbiased estimates of status, trends, and relationships with quantifiable confidence limits over regional and national scales (Hunsaker and Carpenter 1990). The national strategic plan of the FHM program<sup>4</sup> states that Detection Monitoring is designed to identify forest health changes at multiple spatial scales to adequately describe disturbance events that vary in magnitude. Riitters and Tkacz (2004) say that “Detection Monitoring accepts a high rate of false positives (i.e., a high Type I error rate) as the price of not overlooking change (i.e., a low Type II error rate).”

Statistical power analysis (Castelloe 2000) is one practical tool that can be used to evaluate statistical rigor, identify the spatial scale at which an indicator is functional, and address Type I and Type II error rates. This technique clarifies uncertainties about the ability of an indicator to detect a significant effect by examining interactions among the factors contributing to statistical power. Of particular interest to FIA, power analysis can identify areas or situations where sampling intensity is insufficient. Where grid intensification is an option, it can help to establish the appropriate level of intensification. When migrating Phase 3 indicators to the Phase 2 grid is under consideration, it can quantify the benefits to be gained.

Although the application of power analysis to forest health indicators has been under-utilized, it has not been ignored completely. Smith and others (1996) used it to evaluate the benefits of adding an annual overlap to panel rotation schedules when the FHM Program was collecting indicator data. Conkling and others (2002) conducted a power analysis to evaluate the use of FHM mensuration and soils data to detect changes in forest carbon budgets.

The objective of this paper is to evaluate the statistical power of FIA’s Crown-Condition Indicator variables (Schomaker and others 2007) and relate the results to the Phase 3 sampling grid.

## Methods

### Power Analysis

Environmental monitoring often involves hypothesis testing, which is a statistical procedure designed to test the premise that a population displays some

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<sup>4</sup> Available at [http://fhm.fs.fed.us/ann/strategic\\_plan03.pdf](http://fhm.fs.fed.us/ann/strategic_plan03.pdf) [Date accessed: July 28, 2008].

effect ( $H_1$ ), against the null hypothesis that there is no effect ( $H_0$ ). In Detection Monitoring, a typical alternative hypothesis is that there is some difference in indicator values between groups of observations drawn from a population at different points in time. Or the groups may be from the same time period but represent different regions, different species, or stands that have experienced different disturbances.

There are two types of error associated with hypothesis testing. Type I error is a false positive, where the null hypothesis is rejected and the test incorrectly concludes there is some significant effect. The probability of a Type I error is designated as alpha ( $\alpha$ ). The value of  $\alpha$  is selected by the analyst, who decides what the risk of Type I error should be. Alpha commonly is set at 0.05, which restricts the chance of a false positive to 5 percent or less. Type II error is a false negative, where the test misses a true problem by failing to reject a false null hypothesis. The probability of a Type II error is designated as beta ( $\beta$ ). The statistical power of a test is the probability of detecting a difference of a certain magnitude when it indeed exists, and is defined as  $(1 - \beta)$ .

Most statistical tests are designed to minimize  $\alpha$ , while  $\beta$  is often overlooked. Although the consequences of a false positive may be costly in terms of initiating unnecessary Evaluation Monitoring studies, the failure to recognize a significant forest health problem could be disastrous. In Detection Monitoring, it is important to know if the statistical power of an indicator is adequate to support acceptable  $\alpha$  and  $\beta$  probability levels.

We used the SAS POWER procedure (SAS Institute 2004) to examine the relationships among Type I and II error, sample size, data variability, and effect size. We chose the SAS TWOSAMPLEMEANS option to determine the number of plots necessary to detect a difference in mean crown indicator values between two independent samples. Independent samples would come into play when checking for differences among regions during the same time period, or when checking for differences among independent panels<sup>5</sup> at different times. We selected the SAS PAIREDMEANS option to determine the number of plots necessary to detect a difference in mean values between paired observations. The paired approach would be of interest when checking for differences involving survivor trees from re-measured plots.

A variety of input specifications, outputs, and options are available for both the independent and paired procedures. The output of interest for this analysis is the number of plots. The inputs are the  $\alpha$  probability level, the power level  $(1 - \beta)$ , the effect size (mean difference between groups), the underlying data distribution (normal vs. log normal), the standard deviation of the observations; and, for the paired analysis, the correlation coefficient. Any of these input values can be manipulated to determine the subsequent effect on the number of plots required to attain the input specifications. The desired  $\alpha$  probability value, power level, and

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<sup>5</sup> Details about the FIA panelized inventory system are available in Bechtold and Patterson (2005).

effect size are simply specified by the analyst. The underlying data distributions, standard deviations, and correlation coefficients can be estimated from data already on hand, or from a pilot study.

### **Crown-Condition Data**

This analysis focuses on the three main indicators of tree crown health recorded on FIA Phase 3 plots—crown density, foliage transparency, and crown dieback. Crown density is the amount of crown biomass (crown stem, branches, twigs, shoots, buds, foliage, and seeds) that blocks light penetration through the crown. Foliage transparency is the amount of skylight visible through small holes in the live portion of the crown where foliage occurs. Crown dieback is recent mortality of branches with fine twigs that begins at the terminal portion of a branch and proceeds inward toward the trunk. These three indicators are analyzed as continuous variables, although they are actually recorded in 5-percent classes, ranging from 0 to 99 percent. More details about the indicators are available in Schomaker and others (2007); additional details about related FIA sampling protocols are available in the Phase 3 field guide (U.S. Department of Agriculture Forest Service 2007).

The data distributions, standard deviations, and correlation coefficients used in this analysis were obtained from FHM plots measured between 1992 and 1999. FHM data were used because more remeasured plots were available from which to obtain correlation coefficients for paired plots. Although the FHM plot network was integrated into the FIA sampling grid in 2000, some regions still have limited numbers of remeasured panels. For the purpose of power analysis, only approximations of the data attributes are needed, and the measurement protocols for the crown indicators measured by FIA remain unchanged from those used by FHM.

By 1999, the FHM Program was measuring plots in 24 eastern and 8 western States. For the East, the latest measurements of each plot sampled between 1994 and 1999 were used to calculate standard deviations from independent observations. To obtain correlation coefficients from paired observations, the latest measurement of each plot sampled during this period was paired with its previous observation, which was usually 4 years earlier. However, due to differences in the way States and panels were implemented, the remeasurement period was shorter than 4 years in some States. For the West, the latest measurements of each plot sampled between the years 1992 and 1999 were used for the independent observations. Again, the latest observation of each plot measured during this period was paired with its previous observation, which ranged from 1 to 4 years depending on the State. This plot selection method was designed to maximize the numbers of observations available to estimate standard deviations and correlation coefficients of crown indicators by species group; the result was not constrained to represent the actual distribution of species groups in

the populations of eastern and western forests. Correlations were slightly higher between plot pairs measured less than 4 years apart, but judged insufficient to preclude the use of the additional data for the purpose of power analysis.

Power analyses are most commonly applied to experimental designs, but extension of the technique to survey designs is appropriate when the intention is to use survey data for hypothesis testing. Some adaptation was necessary to accommodate FIA's complex design. The ratio-of-mean estimators used by FIA produce variance estimates that accommodate the unbalanced clustering of trees on plots, as well as the use of partial plots in the estimation process (Bechtold and Patterson 2005). However, calculations of standard deviations and correlation coefficients from this design are not as straight-forward. We approximated these statistics by first calculating the mean crown condition for each plot, and then computing the standard deviations and correlation coefficients from the plot-level means. We compared the variance estimates from both methods and obtained similar results, so the simplified approach should have a negligible affect on prospective hypothesis tests and the power analyses associated with them.

## Results

### Crown Density

Crown density in the East averages 47 percent with a standard deviation of 7.5 (table 1). By species group, the means range from 42 to 53 percent, with most standard deviations clustered around 10 or 11. Crown density statistics are similar in the West, except the standard deviations are slightly higher (table 2). Correlation coefficients between paired plots, where mean crown density was computed from survivor trees, are also similar between the two regions—equaling 0.42 in the East and 0.48 in the West. Histograms of data distributions and skewness statistics indicated that crown density was approximately normally distributed.

Table 3 shows the numbers of plots required to detect differences in crown density for various combinations of power-test specifications that conform to the ranges of statistics presented in tables 1 and 2. The effect size (mean difference) was set to detect changes in crown density values from 10 to 15, with standard deviations also fluctuating between 10 and 15. The  $\alpha$  specification alternates from 0.01 to 0.05, and the power level ( $1 - \beta$ ) from 0.8 to 0.9. Given these parameters, the number of plots necessary to detect a change in crown density from independent observations ranges from 18 to 138, depending on the stringency of the specifications. When paired observations are analyzed, the number of plot pairs needed to detect the specified effects ranges from 8 to 54 when the correlation coefficient is 0.25, and from 6 to 37 when the correlation

coefficient is set to 0.5. The SAS code used to produce table 3 is provided in Appendix A.

## Foliage Transparency

Foliage transparency in the East averages 18 percent with a standard deviation of 6 (table 1). By species group, the means range from 13 to 21 percent, with most standard deviations between 5 and 10. The correlation between paired observations was less pronounced than the results for crown density, with a correlation coefficient of 0.19 for all species combined. The correlation coefficients for many species groups were not significant at the 0.05 level. Foliage transparency statistics for the West (table 2) were very similar to the East.

Histograms of the foliage transparency data revealed some skewness caused by outliers in the right tail, and it was not clear whether this variable was normally distributed. Skewness tests indicated that the distribution was not normal, but with large numbers of observations, statistical tests often find deviations from normality that are statistically significant but practically unimportant. Choosing the alternative that yields conservative results is usually the most prudent course of action in borderline cases. We chose the normal classification because more observations were required to attain the specified power than the non-normal alternative. Randolph (2006) also noted that the distribution of this variable was uncertain, but justified a normal classification on the basis that statistical tests are robust against skewness and outliers.

The same  $\alpha$  and power ( $1 - \beta$ ) specifications used for crown density were also used for transparency, but the standard deviations were reduced to 5 and 10 (table 3). The effect size was also reduced to detect changes that fluctuate from 5 to 10 because mean transparency was much smaller than mean crown density (approximately half). Ideally, effect size should be tied to biological thresholds, but none are currently available for many forest health indicators (including the crown variables), so expert judgment must be substituted. Given these specifications, the number of plots necessary to detect a change in foliage transparency from independent observations ranges from 12 to 242. For paired observations, the number of plot pairs needed to detect the specified effects ranges from 6 to 93, when the correlation coefficient is 0.25, and from 5 to 63 when the correlation coefficient is 0.5.

## Crown Dieback

Crown dieback differs from density and transparency in that most trees have little or no dieback, so the data have a severely skewed log normal distribution. Histograms and skewness statistics corroborate this. The SAS POWER procedure

requires different input variables when the underlying data distribution is log normal (see Appendix A). For the specification of effect size, the ratio of the two group means is substituted for the mean difference, and the coefficient of variation (CV) is substituted for the standard deviation.

Dieback in the East averages 4.0 percent with a CV of 1.3 (table 1). By species group, mean dieback varies from 1.6 to 5.9 percent, with CVs ranging from 1.0 to 3.5. Crown dieback means and coefficients of variation are similar in the West (table 2). At 3.3 percent, mean crown dieback is slightly lower in the West because there is a lower proportion of hardwood species there, and dieback tends to be more prevalent in hardwoods.

The same  $\alpha$  and power  $(1 - \beta)$  specifications used previously are used here again, but a relatively large mean ratio is required to detect a meaningful effect when the means are close to 0. The mean ratios were thus set to 2 and 2.5 (specifying changes of 200 and 250 percent), while the CVs varied from 1.5 to 2. Given this input, the number of plots necessary to detect a change in crown dieback from independent observations spans from 48 to 204 (table 3). When paired observations are analyzed, the number of plot pairs needed to detect the specified effects range from 16 to 61 when the correlation coefficient is 0.25, and from 11 to 36 when the correlation coefficient is set to 0.5.

## Relating Results to the FIA Plot Network

Once the number of plots needed to detect a significant difference is known, relating this information to the FIA plot network is simplified by the systematic nature of the grid, where the base sampling intensity is 1 plot per 6,000 acres for Phase 2 and 1 plot per 96,000 acres for Phase 3.

The following formula can use this information to determine how much area must be impacted by a forest health problem before the FIA plot network is able to detect it:

$$IA = n(E) \frac{P_t}{P_n} \quad (1)$$

where

- $IA$  = the minimum size of an impact area detectable by the FIA plot grid in the area of interest,
- $n$  = the number of plots or plot pairs (i.e., grid points) needed to detect an impact (from the power analysis). For independent observations,  $n$  is the number of plots; for paired observations  $n$  is the number of plot pairs.
- $E$  = the plot expansion factor in the area of interest (e.g., 6,000 for Phase 2 or 96,000 for Phase 3),

$P_t$  = the total number of panels per measurement cycle in the area of interest, and  
 $P_n$  = the number of available panels in the area of interest.

When the detectable impact area is known, basic FIA area statistics can be used to evaluate whether the grid intensity is sufficient to recognize the problem. For example, suppose that we want to know if the sampling grid is adequate to detect a change in crown dieback from remeasured plots. Because mean crown dieback is low, usually less than 5 percent, the analyst decides that a doubling of mean crown dieback should not be overlooked. This could mean that a lot more trees have a little dieback, or some subset of trees developed a lot of dieback. Scrutinizing the data from tables 1 and 2, we see that the coefficient of variation for dieback averages about 1.8, and the correlation coefficient between paired observations is usually around 0.3. Plugging these numbers into a power analysis where  $\alpha$  is fixed at .05 and the power ( $1 - \beta$ ) is set to 0.9, we determine that it will take at least 36 plot pairs to flag the specified change as statistically significant. This number can then be used for  $n$  in equation 1. The crown indicator is measured on the Phase 3 plot network, so  $E = 96,000$ . FIA has 5 panels in most Eastern States, so  $P_t = 5$ , and we want the results to apply to a full set of remeasured panels, so  $P_n = 5$ . Entering these values into equation 1 shows there is sufficient power to detect an impact affecting 3.5 million acres of forest (table 4).

The first two columns in table 4 list the current distributions of total land and forest land by region and State from the 2007 RPA statistics<sup>6</sup>. If we divide the detectable impact area for crown dieback (3.5 million acres) by the forest area in column 2, we can see what percentage of the plot grid in a given State or region must be impacted in order to detect a statistically significant difference. Wherever this number is more than 100 percent, the plot grid in the area of interest is not sufficient to detect the specified impact. The sampling intensity for crown dieback is sufficient in most States, but there are several States in the Northeast and in the Great Plains where the grid is obviously insufficient. The sampling intensity of Rhode Island would have to be increased by a factor of 10 to be able to detect the specified change.

Table 4 includes similar analyses for crown density and foliage transparency, where the data in tables 1 and 2 were scrutinized closely to select one set of power-analysis input values that represent a plausible scenario for each crown variable. The input specifications for plausible scenarios for these two variables revealed that 21 plot pairs were needed to detect an unusual change in density, and 31 were needed for transparency. These two variables required fewer plots than crown dieback, but still the grid intensity was not adequate in a few States with relatively little forest.

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<sup>6</sup> Available at <http://fia.fs.fed.us/program-features/rpa/default.asp> [Date accessed: July 28, 2008].

## Discussion

### Adequacy of the Phase 3 Plot Network

When the crown indicators were being developed during the 1990s it was speculated that the sampling intensity was probably adequate for regions or groups of States, but not sufficient to analyze individual States. Results from tables 3 and 4 indicate that about 100 forested plots would be adequate to identify a problem in a majority of prospective change scenarios when independent observations are used. About 50 plots are adequate when using plots with paired observations from two points in time. On the Phase 3 plot network, 50 plots translate into 4.8 million acres. There are 15 States that have less than 4.8 million acres of forest, so each of these States would have to be combined with other States to yield a minimally adequate sample. Considering that crown indicators are often analyzed by species group, and that any given species occurs only on a subset of the total forest plots, then the original conjecture is confirmed that the sampling intensity is not adequate for analysis of many individual States. Power analysis verifies that the FIA plot grid yields an adequate sample at the regional level, with the possible exception of the Great Plains, where 60 percent of the forest would have to be affected. In other regions, less than 4 percent of the forests would need to be impacted in order to detect a problem (table 4).

Equation 1 can be incorporated directly into an Excel spread sheet set up like table 4 to quickly check the adequacy of the sampling grid for a wide variety of scenarios. As presented, table 4 shows how much intensification, if any, is needed in each State to support analyses at the State level. This information can be used to guide State-level intensifications. Moving some of the forest health indicators to the Phase 2 sampling grid has lately been of interest. Changing the expansion factor ( $E$ ) in equation 1 from 96,000 to 6,000 yields a measure of the additional power to be gained from this modification.

The detectable impact areas in table 4 are based on a full complement of panels. At current rates of implementation it takes 5 to 10 years (depending on the State and region) to obtain a complete measurement cycle, and twice as long to obtain paired observations. So there is a period of vulnerability where sample size may be inadequate during the 10 to 20 years needed to ramp up to a full complement of remeasured panels. Equation 1 can be used to investigate the issue by reducing the number of panels available for analysis.

The grid adequacy examples discussed so far are all related to the overall grid, where plots are contiguous over States and regions. The power analysis can be refined to more specific, non-contiguous plots by applying equation 1 to almost any FIA area table, such as area by forest type. This approach informs the analyst if there is enough power to analyze a specific forest type (or any other area-related attribute such as elevation or disturbance history).

The detectable impact areas discussed thus far are based on forest area. The detectable impact area can be converted to total land area by dividing the detectable forest area by the percentage of forest in the area of interest. For example, 3.5 million acres of *forest* must be impacted by the crown dieback example in table 4. This means that a problem which is not confined to forests (e.g., climate change) must be impacting a larger area than just the forest. In the Northeast, where the forests constitute 67 percent of the total land area, about 5.2 million acres of total land area must be affected to recognize the problem. This information could be used in simulation models, where the FIA grid might be checked for adequacy to recognize problems dispersed across the total landscape.

## Independence

FIA plots can contribute observations to more than one group, so it is important to consider whether the groups being compared consist of independent, paired, or mixed observations. Independence is guaranteed only when the groups are drawn from mutually exclusive sets of plots, which is usually the case when comparing different regions or different panels. Purely paired analyses are achieved only when each plot is required to contribute an observation to both groups, which is commonly the case when the groups are based on survivor trees from plots measured at two points in time. In other situations, the groups will be a mixture of independent and paired observations. For example, a plot can experience multiple disturbances. For an analysis designed to compare two disturbances, a single plot has the potential to contribute an observation to one or both disturbance groups, resulting in a mixture.

The SAS TWOSAMPLEMEANS option is most appropriate for independent observations, but setting the correlation coefficient to 0 in the PAIREDMEANS option yields approximately the same result. So PAIREDMEANS can be modified to accommodate mixtures of independent and paired observations by adjusting the correlation coefficient. For example, if 40 percent of the observations in a prospective analysis are expected to be paired, the correlation coefficient could be reduced to 40 percent of the value that would be used if all plots were paired. Keep in mind when interpreting results that PAIREDMEANS presents output in terms of plot pairs (*npairs*). When mixtures of independent and paired plots are analyzed with PAIREDMEANS, the total number of grid points (i.e., independent plots plus plot pairs) necessary to support the analysis can be calculated by adjusting *npairs* for the proportion of paired plots:

$$n = 2(npairs)(1 - prop) + (npairs)(prop) \quad (2)$$

where

*npairs* = the number of paired plots output from PAIREDMEANS, and

*prop* = the expected proportion of paired plots in a prospective analysis.

All of the results presented here assume that numbers of observations are balanced between groups. Statistical power decreases as designs become unbalanced. This is not an issue with paired observations, but FIA's survey design can become unbalanced when analyses are based on independent or mixed observations. For independent observations, the TWOSAMPLEMEANS procedure has a weighting feature to accommodate unbalanced designs. This feature is not available with PAIREDMEANS, so the effects of an unbalanced design are not readily obtainable when mixtures of independent and paired observations are processed with PAIREDMEANS. Sensitivity to imbalance can be approximated with TWOSAMPLEMEANS, and estimated power reductions could then be extrapolated to results from PAIREDMEANS. For example, the number of plots required for independent observations in table 3 increases by an average of 11 percent when the sample size in each group is unbalanced by a ratio of 2:1. The number of plots resulting from a similar analysis of mixed observations with PAIREDMEANS would then be increased by this percent.

### **Strategies to Increase Statistical Power**

Increasing sample size is one obvious way to gain statistical power. Grid intensification is the preferred approach if economically feasible. Sample size can also be increased by combining areas, but this must be done carefully. Adding adjacent States will increase power if those areas have the same problem as the original location. If not, the analysis could be compromised because adding unaffected areas will dilute any effect that may have been present at the original location. Sometimes adding more territory is not an option. For example, Hawaii is so isolated that it would not be practical to combine Hawaii with any other State. Given this, it is noteworthy that the base Phase 3 sampling intensity in Hawaii would not support an analysis of crown indicators (table 4).

Power can also be gained by tailoring analyses to more specific subsets of the data through stratification. Forest health impacts that have "clumped" distributions display a higher variance than impacts that are evenly dispersed. Statistical power is adversely affected by increased variance. Stratification can help by reducing variation within strata. If a clumped distribution is suspected, post-stratify the data to isolate the clumps if possible.

Power might be gained by taking advantage of the "double sampling for stratification" technique that FIA uses for standard inventory estimates (Bechtold and Patterson 2005). This technique reduces the variance of many FIA inventory estimates, and variance reduction always increases statistical power. However, the Phase 3 indicators have not yet been incorporated into FIA's processing engine, so the degree to which this procedure might reduce the variance of crown indicators is uncertain.

Species groups are another important aspect of stratification. Grouping species together has the potential to increase power by increasing the number of plots available for analysis, but a forest health problem that impacts only a few species in a group may go undetected. If a particular species is known to be sensitive to a prospective threat, that species should be isolated. Care must always be taken to avoid different species mixes between the two groups of observations being tested, because effect size could be an artifact of the difference in species mix.

The results presented here are based on two-tailed tests, where the alternate hypothesis ( $H_1$ ) is that the mean of Group 1 differs from the mean of Group 2, so the analyst can determine whether an indicator is improving or deteriorating. Additional power can be attained by using one-tailed tests, where  $H_1$  is modified to specify that the mean of Group 2 has either increased or decreased. On average, when one-tailed tests are used, the number of plots is reduced to 83 percent of the required observations listed in table 3. Note that the alternative hypotheses ( $H_1$ ) should be specified prior to any testing. It is not valid to look at the data and then decide if the variable of interest should be increasing or decreasing.

## Conclusions

Comprehensive power analyses of FIA's Phase 3 indicators are possible with only three pieces of information derived from actual data—the indicator's frequency distribution (normal vs. log normal), its standard deviation, and a correlation coefficient for paired observations. The analyst can then solve for detectable effect size,  $\alpha$  level, statistical power ( $1 - \beta$ ), or numbers of observations required. Supplied with the number of plots required to detect a significant effect, the adequacy of the FIA grid to support prospective analyses can be readily evaluated.

For most plausible scenarios involving the crown indicator, about 100 plots (or 50 paired plots) would be adequate. Paired plots resulting from repeated observations over time reduces the number of grid points to less than half the observations that would be required from independent observations. These results are consistent with previously unverified assumptions that the crown indicators as implemented on the Phase 3 grid could reliably support analyses at the regional level, but probably not for many individual States.

We recommend that power analyses be conducted for all indicators where statistical hypothesis testing is an option. The information needed to accomplish this is readily available from existing datasets for indicators that have already been implemented. As new indicators are proposed, power analysis should become a formal part of the indicator development process.

## Literature Cited

- Alexander, S.A.; Palmer, C.J. 1999. Forest Health Monitoring in the United States: first four years. *Environmental Monitoring and Assessment* 55: 267-277.
- Bechtold, W.A.; Patterson, P.L. eds. 2005. The enhanced Forest Inventory and Analysis Program—national sampling design and estimation procedures. Gen. Tech. Rep. SRS-80. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 85 p.
- Castelloe, J.M. 2000. Sample Size Computations and Power Analysis with the SAS System Paper 247. Cary, NC: SAS Institute. Available at: <http://www.ats.ucla.edu/stat/sas/library/powersamplesize.pdf> [Date accessed: July 28, 2008].
- Conkling, B.L.; Hoover, C.M.; Smith, W.D.; Palmer, C.J. 2002. Using forest health monitoring data to integrate above and below ground carbon information. *Environmental Pollution: Vol. 116, Supplement 1, March 2002, Pages S221-S232.*
- Hunsaker, C.T.; Carpenter, D.E. (Eds.), 1990. Environmental Monitoring and Assessment Program. Ecological Indicators. EPA 600/3-90/060. US Environmental Protection Agency, Office of Research and Development, Research Triangle Park, NC.
- Randolph, K.C. 2006. Descriptive statistics of tree crown condition in the Southern United States and impacts on data analysis and interpretation. Gen. Tech. Rep. SRS-94. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 17 p.
- Riitters, K.; Tkacz, B. 2004. Forest health monitoring. pp. 669-683 in Wiersma, B., ed. *Environmental Monitoring*. CRC Press, Boca Raton, FL. 792 p.
- SAS Institute Inc. 2004. SAS OnlineDoc® 9.1.3. Cary, NC: SAS Institute Inc.
- Schomaker, M.E.; Zarnoch, S.J.; Bechtold, W.A.; Latelle, D.J.; Burkman, W.G.; Cox, S. M. 2007. Crown-condition classification: a guide to data collection and analysis. Gen. Tech. Rep. SRS-102. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 78 p.
- Smith, W.D.; Gumpertz, M.L.; Catts, G.C. 1996. An analysis of the precision of change estimation of four alternative sampling designs for forest health monitoring. Forest Health Monitoring Tech. Rep. Series. Research Triangle Park, NC: Forest Health Monitoring National Office. 24 p.
- Turner, J.A.; Oswalt, C.M.; Chamberlain, J.L [and others]. 2008. Kentucky's Forests, 2004. Resour. Bull. SRS-129. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 101 p.
- U.S. Department of Agriculture Forest Service. 2007. Forest Inventory and Analysis National Core Field Guide (Phase 3), version 4.0. Washington, DC: U.S. Department of Agriculture Forest Service, Forest Inventory and Analysis, Washington, D.C.

Available at: <http://socrates.lv-hrc.nevada.edu/fia/dab/databandindex.html#4.%20%20Current%20National%20Core%20Field> [Date accessed: July 28, 2008].

## Appendix A. SAS Power Analysis Program

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/*
```

This SAS program performed the Power Analysis resulting in Table 3.

This program produces numbers of observations (ntotal or npairs) as the dependent variable. The analysis can be revised to make any of the associated variables (power, alpha, stddev, cv, meandiff, meanratio, or corr) into the dependent variable by specifying the number of observations available and setting the dependent variable of interest to null.

```
*/
```

```
title1 'Crown Density - independent observations';
```

```
proc power; twosamplemeans
  outputorder = syntax
  test        = diff
  dist        = normal
  power       = .80 .90
  alpha       = .01 .05
  stddev      = 10 15
  meandiff    = 10 15
  ntotal      = .
;
```

```
title1 'Foliage Transparency - independent observations';
```

```
proc power; twosamplemeans
  outputorder = syntax
  test        = diff
  dist        = normal
  power       = .80 .90
  alpha       = .01 .05
  stddev      = 5 10
  meandiff    = 5 10
  ntotal      = .
;
```

```
title1 'Crown Dieback - independent observations';
```

```
proc power; twosamplemeans
  outputorder = syntax
  test        = ratio
  dist        = lognormal
  power       = .80 .90
  alpha       = .01 .05
  cv          = 1.5 2
  meanratio   = 2 2.5
  ntotal      = .
;
```

```
title1 'Crown Density - paired observations';
proc power; pairedmeans
outputorder = syntax
test      = diff
dist      = normal
corr      = .25 .5
power     = .80 .90
alpha     = .01 .05
stddev    = 10 15
meandiff  = 10 15
npairs    = .
;

title1 'Foliage Transparency - paired observations';
proc power; pairedmeans
outputorder = syntax
test      = diff
dist      = normal
corr      = .25 .5
power     = .80 .90
alpha     = .01 .05
stddev    = 5 10
meandiff  = 5 10
npairs    = .
;

title1 'Crown Dieback - paired observations';
proc power; pairedmeans
outputorder = syntax
test      = ratio
dist      = lognormal
corr      = .25 .5
power     = .80 .90
alpha     = .01 .05
cv        = 1.5 2
meanratio = 2 2.5
npairs    = .
; run;
```

**Table 1.** Means (m), standard deviations (s), coefficients of variation (cv), and correlation coefficients (r) of crown data collected by the Forest Health Monitoring Program in 24 eastern States<sup>a</sup>, by species group, 1994-1999.

Species Group	Independent <sup>b</sup> observations		Paired <sup>c,d</sup> observations		Crown density			Foliage transparency			Crown dieback		
	n	n	n	n	m	s	r <sup>e</sup>	m	s	r <sup>e</sup>	m	cv	r <sup>e</sup>
	trees	plots	trees	plots									
Softwoods:													
South. yellow pine	6,648	441	2,729	219	42.1	8.6	0.37 *	18.8	7.1	0.41 *	2.1	1.9	0.46 *
East. white pine	1,157	180	604	99	48.6	10.6	0.51 *	20.4	5.8	0.29 *	2.7	1.5	0.72 *
Red pine	521	37	347	27	50.3	10.5	0.31	18.4	4.0	0.24	1.6	1.5	0.08
Spruce/fir	2,459	258	1,720	193	51.6	10.3	0.61 *	16.7	4.6	0.21 *	4.4	1.5	0.18 *
Hemlock	776	130	408	69	53.1	10.8	0.64 *	17.7	5.7	0.35 *	3.0	1.3	0.67 *
Other Softwoods	1,867	241	1,462	142	48.5	13.7	0.36 *	19.4	7.1	0.27 *	5.0	1.6	0.38 *
Hardwoods:													
Oak	6,088	855	2,532	410	47.0	8.4	0.32 *	17.0	6.2	0.15 *	4.2	1.3	0.24 *
Elm	576	228	229	99	44.1	11.1	0.30 *	20.2	7.8	0.30 *	5.9	1.9	0.35 *
Hickory	1,196	391	401	137	51.5	10.4	0.48 *	14.8	6.3	-0.06	2.5	2.3	0.14
Birch	1,724	416	1,043	263	50.6	9.9	0.40 *	18.0	5.4	0.15 *	4.5	1.1	0.28 *
Maple	6,481	916	3,428	502	48.4	9.1	0.46 *	16.8	5.5	0.15 *	3.9	1.5	0.55 *
Beech	730	201	320	95	51.1	11.6	0.58 *	15.3	4.5	0.17	3.7	1.5	0.30 *
Sweetgum	1,032	262	440	126	48.2	10.9	0.41 *	13.4	5.7	0.24 *	3.0	2.5	-0.01
Tupelo-blackgum	690	237	341	102	47.1	11.8	0.62 *	16.1	9.5	0.03	3.5	2.9	0.81 *
Ash	1,303	340	680	168	46.7	11.6	0.50 *	19.0	8.4	0.67 *	5.0	2.1	0.82 *
Quaking Aspen	1,113	192	801	136	47.2	10.3	0.45 *	21.4	5.7	0.07	4.9	1.0	0.51 *
Basswood	388	98	277	63	48.3	10.7	0.44 *	18.4	6.1	-0.10	4.1	2.2	0.24
Yellow Poplar	1,022	282	498	141	51.7	10.2	0.16	15.3	7.7	0.08	2.1	3.5	0.20 *
Walnut	114	65	44	27	44.4	12.9	0.51 *	19.3	11.6	0.57 *	5.3	3.1	0.00
Other Hardwoods	2,900	770	1,310	367	45.5	10.6	0.36 *	18.9	8.1	0.12 *	4.5	1.9	0.18 *
All softwoods	13,428	957	7,270	549	46.9	10.8	0.58 *	18.6	6.4	0.37 *	3.0	1.6	0.46 *
All hardwoods	25,357	1,515	12,344	813	47.7	7.8	0.43 *	17.4	6.3	0.35 *	4.5	1.5	0.47 *
All species	38,785	1,625	19,614	890	47.2	7.5	0.42 *	17.7	5.6	0.19 *	4.0	1.3	0.36 *

<sup>a</sup> States included: AL, CT, DE, GA, IL, IN, ME, MD, MA, MI, MN, MO, NH, NJ, NY, NC, PA, RI, SC, TN, VT, VA, WV, and WI.

<sup>b</sup> Independent observations from the latest set of 4 panels sampled between 1994 and 1999 in each State were used to calculate means (m), standard deviations (s), and coefficients of variation (cv).

<sup>c</sup> Paired observations from the latest set of re-measured panels sampled between 1994 and 1999 in each State. Plot means from survivor trees were paired with their previous values to calculate correlation coefficients (r). The number of re-measured panels available varies by State.

<sup>d</sup> The numbers of observations represent pairs. The total numbers of observations are twice the listed numbers of pairs.

<sup>e</sup> Asterisks indicate significant correlation coefficients, where p-values are  $\leq .05$ .

**Table 2.** Means, standard deviations (s), coefficients of variation (cv), and correlation coefficients (r) of crown data collected by the Forest Health Monitoring Program in 8 western States<sup>a</sup>, by species group, 1992-1999.

Species Group	Independent <sup>b</sup> observations		Paired <sup>c,d</sup> observations		Crown density			Foliage transparency			Crown dieback		
	n	n	n	n	m	s	r <sup>e</sup>	m	s	r <sup>e</sup>	m	cv	r <sup>e</sup>
	trees	plots	trees	plots									
Softwood timberland:													
Douglas fir	3,932	380	2,003	219	50.8	11.4	0.43 *	14.5	4.0	0.10	1.8	1.8	0.23 *
Ponderosa pine	1,467	192	985	134	46.4	11.4	0.42 *	17.3	6.1	0.24 *	2.1	2.9	0.08
True fir	3,084	315	1,915	204	51.6	12.4	0.43 *	13.5	4.6	0.11	2.6	1.7	0.48 *
Western hemlock	962	85	455	45	51.5	10.7	0.38 *	13.9	3.4	0.12	1.7	1.8	0.52 *
Sugar pine	102	27	76	22	47.8	9.6	0.25	18.1	6.9	0.03	1.1	2.0	-0.21
Western white pine	82	30	46	17	48.8	12.2	0.69 *	18.4	5.3	0.58 *	3.8	1.4	0.65 *
Spruce	1,255	138	870	90	50.7	10.5	0.42 *	12.3	4.2	-0.02	2.1	1.3	0.29 *
Western larch	173	38	77	22	50.1	14.3	0.36	20.0	5.9	-0.06	2.2	1.5	0.40
Incense cedar	209	41	179	33	47.3	13.4	0.47 *	15.8	4.7	0.17	1.5	2.5	0.05
Lodgepole pine	2,818	166	2,011	108	43.6	10.0	0.51 *	16.3	4.1	0.17	3.0	1.3	0.51 *
Western red cedar	431	54	237	29	48.6	12.8	0.49 *	18.1	5.8	0.26	1.7	1.9	0.37 *
Other softwoods	702	126	396	82	43.5	12.9	0.63 *	16.3	7.2	0.46 *	3.0	1.9	0.20
Softwood woodland	3,321	270	961	100	51.8	13.7	0.64 *	12.3	4.2	0.40 *	4.3	1.4	0.14
Hardwood timberland:													
Quaking aspen	1,246	83	852	51	36.0	9.0	0.06	21.3	6.2	-0.05	5.2	1.6	0.31 *
Cottonwood/poplar	69	11	64	9	47.9	11.1	0.56	17.6	6.9	0.54	2.4	1.0	0.04
Red alder	363	42	203	18	48.5	14.4	0.19	23.3	13.1	-0.10	5.2	2.8	0.32
Timberland oak	1,068	106	874	91	38.0	10.3	0.52 *	18.8	8.5	-0.07	5.8	1.7	0.41 *
Other hardwoods	921	100	628	63	43.3	12.1	0.18	19.1	8.1	-0.05	4.4	2.1	-0.04
Hardwood woodland	3,321	86	125	29	43.2	14.5	0.58 *	18.2	7.4	-0.10	7.8	1.5	0.66 *
All softwoods	18,538	927	10,211	526	49.5	11.0	0.49 *	14.4	4.8	0.28 *	2.8	1.4	0.20 *
All hardwoods	4,310	361	2,746	219	41.0	11.8	0.30 *	19.5	7.6	0.01	5.6	1.6	0.46 *
All species	22,848	1,000	12,957	581	47.2	11.1	0.48 *	15.0	5.1	0.18 *	3.3	1.3	0.35 *

<sup>a</sup> States included: CA, CO, ID, NV, OR, UT, WA, and WY.

<sup>b</sup> Independent observations from the latest set of 4 panels sampled between 1992 and 1999 in each State were used to calculate means (m), standard deviations (s), and coefficients of variation (cv).

<sup>c</sup> Paired observations from the latest set of re-measured panels sampled between 1992 and 1999 in each State. Plot means from survivor trees were paired with their previous values to calculate correlation coefficients (r).

The number of re-measured panels available varies by State.

<sup>d</sup> The numbers of observations represent pairs. The total numbers of observations are twice the listed numbers of pairs.

<sup>e</sup> Asterisks indicate significant correlation coefficients, where p-values are  $\leq .05$ .

**Table 3.** Numbers of independent and paired observations required to detect a statistically significant signal, given the listed combinations of input specifications for 3 crown variables (crown density, foliage transparency, and crown dieback).

Variable	Power analysis input specifications					Plots required		
	Data Distribution	Power level (1-B)	Alpha level (α)	Data variability <sup>a</sup>	Effect size <sup>b</sup>	Independent	Paired <sup>c,d</sup>	
						n plots	n plots (r=.25)	n plots (r=.50)
Crown density	Normal	0.8	0.01	10	10	52	21	16
		0.8	0.01	10	15	26	12	9
		0.8	0.01	15	10	110	43	30
		0.8	0.01	15	15	52	21	16
		0.8	0.05	10	10	34	14	10
		0.8	0.05	10	15	18	8	6
		0.8	0.05	15	10	74	29	20
		0.8	0.05	15	15	34	14	10
		0.9	0.01	10	10	64	26	19
		0.9	0.01	10	15	30	14	11
		0.9	0.01	15	10	138	54	37
		0.9	0.01	15	15	64	26	19
		0.9	0.05	10	10	46	18	13
		0.9	0.05	10	15	22	10	7
		0.9	0.05	15	10	98	38	26
0.9	0.05	15	15	46	18	13		
Foliage transparency	Normal	0.8	0.01	5	5	52	21	16
		0.8	0.01	5	10	16	8	7
		0.8	0.01	10	5	192	74	51
		0.8	0.01	10	10	52	21	16
		0.8	0.05	5	5	34	14	10
		0.8	0.05	5	10	12	6	5
		0.8	0.05	10	5	128	50	34
		0.8	0.05	10	10	34	14	10
		0.9	0.01	5	5	64	26	19
		0.9	0.01	5	10	20	10	8
		0.9	0.01	10	5	242	93	63
		0.9	0.01	10	10	64	26	19
		0.9	0.05	5	5	46	18	13
		0.9	0.05	5	10	14	7	5
		0.9	0.05	10	5	172	65	44
0.9	0.05	10	10	46	18	13		
Crown dieback	Log normal	0.8	0.01	1.5	2	118	39	25
		0.8	0.01	1.5	2.5	70	24	16
		0.8	0.01	2.0	2	160	48	29
		0.8	0.01	2.0	2.5	94	29	18
		0.8	0.05	1.5	2	80	26	16
		0.8	0.05	1.5	2.5	48	16	11
		0.8	0.05	2.0	2	108	32	19
		0.8	0.05	2.0	2.5	64	20	12
		0.9	0.01	1.5	2	150	49	30
		0.9	0.01	1.5	2.5	88	30	19
		0.9	0.01	2.0	2	204	61	36
		0.9	0.01	2.0	2.5	118	36	22
		0.9	0.05	1.5	2	106	35	21
		0.9	0.05	1.5	2.5	62	21	13
		0.9	0.05	2.0	2	144	43	25
0.9	0.05	2.0	2.5	84	25	15		

<sup>a</sup> For variables with a normal distribution the measure of data variability is the standard deviation. For variables with a log normal distribution the measure of data variability is the coefficient of variation.

<sup>b</sup> For variables with a normal distribution the effect size is specified as the difference between two means. For variables with a log normal distribution the effect size is specified as the ratio between two means.

<sup>c</sup> Paired observations require the additional specification of a correlation coefficient (r). These results show the numbers of observations required when the correlation coefficient is set to 0.25 and 0.50.

<sup>d</sup> The numbers of plots listed represent pairs. Each pair represents 1 plot (i.e., grid point) with two observations.

**Table 4.** Total land area, forest land area, and detectable impact area for three crown-indicator scenarios involving remeasured (paired) plots, by region and State.

Region / State	RPA area <sup>a</sup>		Detectable impact area <sup>b</sup>					
	Total land	Forest land	Crown density <sup>c</sup> (21 paired plots)		Foliage transparency <sup>d</sup> (31 paired plots)		Crown dieback <sup>e</sup> (36 paired plots)	
			Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>	Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>	Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>
	----- M acres -----		M acres	Percent	M acres	Percent	M acres	Percent
<b>Northeast:</b>								
Connecticut	3,101	1,794	2,016	112	2,976	166	3,456	193
Delaware	1,251	383	2,016	527	2,976	777	3,456	903
Maine	19,752	17,673	2,016	11	2,976	17	3,456	20
Maryland	6,256	2,566	2,016	79	2,976	116	3,456	135
Massachusetts	5,018	3,171	2,016	64	2,976	94	3,456	109
New Hampshire	5,740	4,850	2,016	42	2,976	61	3,456	71
New Jersey	4,748	2,132	2,016	95	2,976	140	3,456	162
New York	30,217	18,669	2,016	11	2,976	16	3,456	19
Pennsylvania	28,683	16,577	2,016	12	2,976	18	3,456	21
Rhode Island	669	356	2,016	567	2,976	836	3,456	971
Vermont	5,920	4,618	2,016	44	2,976	64	3,456	75
West Virginia	15,415	12,007	2,016	17	2,976	25	3,456	29
<b>Total</b>	<b>126,767</b>	<b>84,796</b>	<b>2,016</b>	<b>2</b>	<b>2,976</b>	<b>4</b>	<b>3,456</b>	<b>4</b>
<b>North Central:</b>								
Illinois	35,608	4,525	2,016	45	2,976	66	3,456	76
Indiana	22,980	4,656	2,016	43	2,976	64	3,456	74
Iowa	35,842	2,879	2,016	70	2,976	103	3,456	120
Michigan	36,275	19,545	2,016	10	2,976	15	3,456	18
Minnesota	51,024	16,391	2,016	12	2,976	18	3,456	21
Missouri	44,093	15,078	2,016	13	2,976	20	3,456	23
Ohio	26,207	7,894	2,016	26	2,976	38	3,456	44
Wisconsin	34,791	16,275	2,016	12	2,976	18	3,456	21
<b>Total</b>	<b>286,819</b>	<b>87,243</b>	<b>2,016</b>	<b>2</b>	<b>2,976</b>	<b>3</b>	<b>3,456</b>	<b>4</b>
<b>South:</b>								
<b>Southeast:</b>								
Florida	35,026	16,147	2,016	12	2,976	18	3,456	21
Georgia	37,114	24,784	2,016	8	2,976	12	3,456	14
North Carolina	31,128	18,447	2,016	11	2,976	16	3,456	19
South Carolina	19,207	12,746	2,016	16	2,976	23	3,456	27
Virginia	25,626	15,766	2,016	13	2,976	19	3,456	22
<b>Total</b>	<b>148,102</b>	<b>87,889</b>	<b>2,016</b>	<b>2</b>	<b>2,976</b>	<b>3</b>	<b>3,456</b>	<b>4</b>
<b>South Central:</b>								
Alabama	32,435	22,693	2,016	9	2,976	13	3,456	15
Arkansas	33,324	18,830	2,016	11	2,976	16	3,456	18
Kentucky	25,426	11,970	2,016	17	2,976	25	3,456	29
Louisiana	27,880	14,222	2,016	14	2,976	21	3,456	24
Mississippi	30,026	19,622	2,016	10	2,976	15	3,456	18
Oklahoma	43,954	7,665	2,016	26	2,976	39	3,456	45
Tennessee	26,390	14,480	2,016	14	2,976	21	3,456	24
Texas	167,693	17,273	2,016	12	2,976	17	3,456	20
<b>Total</b>	<b>387,127</b>	<b>126,756</b>	<b>2,016</b>	<b>2</b>	<b>2,976</b>	<b>2</b>	<b>3,456</b>	<b>3</b>
<b>Great Plains:</b>								
Kansas	52,488	2,106	2,016	96	2,976	141	3,456	164
Nebraska	49,206	1,245	2,016	162	2,976	239	3,456	278
North Dakota	44,337	724	2,016	278	2,976	411	3,456	477
South Dakota	48,434	1,682	2,016	120	2,976	177	3,456	205
<b>Total</b>	<b>194,465</b>	<b>5,757</b>	<b>2,016</b>	<b>35</b>	<b>2,976</b>	<b>52</b>	<b>3,456</b>	<b>60</b>

Continued...

**Table 4 continued.** Total land area, forest land area, and detectable impact area for three crown-indicator scenarios involving remeasured (paired) plots, by region and State.

Region / State	RPA area <sup>a</sup>		Detectable impact area <sup>b</sup>					
	Total land	Forest land	Crown density <sup>c</sup> (21 paired plots)		Foliage transparency <sup>d</sup> (31 paired plots)		Crown dieback <sup>e</sup> (36 paired plots)	
			Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>	Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>	Forest Area <sup>f</sup>	Percent Forest <sup>g</sup>
	----- M acres -----	M acres	M acres	Percent	M acres	Percent	M acres	Percent
Intermountain:								
Arizona	72,764	18,671	2,016	11	2,976	16	3,456	19
Colorado	66,390	22,612	2,016	9	2,976	13	3,456	15
Idaho	52,909	21,430	2,016	9	2,976	14	3,456	16
Montana	93,306	25,014	2,016	8	2,976	12	3,456	14
Nevada	70,446	11,089	2,016	18	2,976	27	3,456	31
New Mexico	77,674	16,682	2,016	12	2,976	18	3,456	21
Utah	52,497	17,962	2,016	11	2,976	17	3,456	19
Wyoming	62,062	11,445	2,016	18	2,976	26	3,456	30
Total	548,047	144,905	2,016	1	2,976	2	3,456	2
Pacific Northwest:								
Oregon	61,181	30,169	2,016	7	2,976	10	3,456	11
Washington	42,609	22,279	2,016	9	2,976	13	3,456	16
California	99,599	32,817	2,016	6	2,976	9	3,456	11
Hawaii	4,111	1,748	2,016	115	2,976	170	3,456	198
Alaska	365,042	126,869	2,016	2	2,976	2	3,456	3
Total	572,542	213,883	2,016	1	2,976	1	3,456	2

<sup>a</sup> Source: 2007 RPA statistics (<http://fia.fs.fed.us/program-features/rpa/default.asp>).

<sup>b</sup> The forest area that must be impacted in order to detect a forest health problem, given a specified number of plots.

<sup>c</sup> 21 paired plots are necessary to detect a significant change given: a normal data distribution; power level (1-B)=0.9; a=0.05; standard deviation=12; correlation coefficient=0.4; mean difference=10.

<sup>d</sup> 31 paired plots are necessary to detect a significant change given: a normal data distribution; power level (1-B)=0.9; a=0.05; standard deviation=6.5; correlation coefficient=0.2; mean difference=5.

<sup>e</sup> 36 paired plots are necessary to detect a significant change given: a log normal data distribution; power level (1-B)=0.9; a=0.05; coefficient of variation=1.8; correlation coefficient=0.3; ratio of mean difference=2.

<sup>f</sup> Impact area=n(E)\*(Pn/Pt) where n = the specified number of plots; E=plot expansion factor=96,000; Pn=available panels=5; Pt=total panels=5.

<sup>g</sup> Percent forest impact area = detectable forest impact area / forest area \* 100. This is the percentage of forest area in the listed State or region that must be impacted by a disturbance in order to detect a significant change. Values greater than 100 indicate that the sampling intensity is insufficient.