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A statistical power analysis of woody carbon flux from forest inventory data

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Abstract At a national scale, the carbon (C) balance of numerous forest ecosystem C pools can be monitored using a stock change approach based on national forest inventory data. Given the potential influence of disturbance events and/or climate change processes, the statistical detection of changes in forest C stocks is paramount to maintaining the net sequestration status of these stocks. To inform the monitoring of forest C balances across large areas, a power analysis of a forest inventory of live/dead standing trees and downed dead wood C stocks (and components thereof) was performed in states of the Great Lakes region, U.S. Using data from the Forest Inventory and Analysis (FIA) program of the U.S. Forest Service, it was found that a decrease in downed wood C stocks (−1.87 Mg/ha) was nearly offset by an increase in standing C stocks (1.77 Mg/ha) across the study region over a 5-year period. Carbon stock change estimates for downed dead wood and standing pools were statistically different from zero (α=0.10), while the net change in total woody C (−0.10 Mg/ha) was not statistically different from zero. To obtain a statistical power to detect change of 0.80 (α=0.10), standing live C stocks must change by at least 0.7 %. Similarly, standing dead C stocks would need to change by 3.8 %; while downed dead C stocks require a change of 6.9 %. While the U.S.'s current forest inventory design and sample intensity may not be able to statistically detect slight changes (<1 %) in forest woody C stocks at sub-national scales, large disturbance events (>3 % stock change) would almost surely be detected. Understanding these relationships among change detection thresholds, sampling effort, and Type I (α) error rates allows analysts to evaluate the efficacy of forest inventory data for C pool change detection at various spatial scales and levels of risk for drawing erroneous conclusions.

1 Introduction

Globally, there has been burgeoning interest in monitoring changes in forest ecosystem carbon (C) stocks as a means to offset Greenhouse Gas (GHG) emissions and thus perhaps

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mitigate climate change (Ryan et al. 2010; Pan et al. 2011). Terrestrial forest C pools, such as standing live trees and detrital components (i.e., downed woody material; DWM), often represent a tenuous balance between the influx of CO_2 fixed in photosynthesis and the efflux of CO_2 through woody decay and combustion processes (Malhi et al. 1999). Future climate change may alter this balance through large-scale disturbance events (Dale et al. 2001). It is possible that forest ecosystems could become net emitters of GHGs if extreme disturbance events occur (e.g., ecosystem-scale insect outbreaks; Kurz et al. 2008).

While small-scale studies of C flux are imperative for understanding processes that affect C sink/source dynamics, landscape-scale assessments are needed to understand current net C flux in forest ecosystems and inform policy and management decisions. As countries develop forest C monitoring strategies aimed at providing stock estimates of diverse forest components, the question arises: What level of statistical power to detect change do these inventories possess? The inability to identify C flux in forest ecosystems may lead to erroneous assessments of risk and delay in development and implementation of climate change mitigation strategies (Yohe 2009; Iverson et al. 2012). Indeed, accurately gauging trends in forest C stocks and effects of disturbance events is paramount to the science of climate change (Reich 2011).

In the context of trends in C sequestration and emission, the ability to detect changes over time is of equal or greater importance than having precise estimates of current values. Generally, inability to detect change (i.e., Type II error) is considered more egregious in environmental monitoring because failure to recognize (and perhaps respond to) changing conditions is often more deleterious than taking action to correct a perceived change that did not actually occur (i.e., Type I error) (Fairweather 1991; Mapstone 1995). In practice, commission of either error type remains unidentified as the true population values are unknown. As such, low Type I (α) and Type II (β) error rates are sought to minimize the probability of drawing erroneous conclusions. The conundrum faced by C inventory analysts is that Type I and Type II errors are inversely related, such that for a given sample size, the Type II error rate increases if the Type I rate is decreased and vice versa (Kleinbaum et al. 2008).

Assessments of C stocks over large spatial extents can be made by national-scale forest inventory and monitoring efforts, such as those implemented by the Forest Inventory and Analysis (FIA) program of the U.S. Forest Service. The FIA inventory is the basis for the U.S.'s forest C inventory (US EPA 2011) and has estimated that 44 % of the total forest C pool in the U.S. is in standing vegetation, 38 % in the soil, and 18 % in dead organic material, such as dead wood and the forest floor (Heath et al. 2011). The ability to detect change in woody C pools from the FIA inventory has not been evaluated. The detection of forest ecosystem C stock change is complicated by their inherent diversity (i.e., from live trees to soil organic carbon) and sampling intensities that were developed using precision requirements for forest attributes other than C pools (e.g., current status of traditional forest ecosystem attributes such as merchantable tree volume).

Overall, statistically-robust monitoring of changes in forest C stocks via empirical assessments of forest inventory data is critical to assessing the impact of disturbance/management effects on U.S. C stocks and the potential influence of climate change on associated C balances. In this paper, we evaluated the statistical power (1-β) to detect changes in standing live/dead aboveground and DWM C pools (and aggregates thereof) using forest inventory data from Michigan, Minnesota, and Wisconsin (Great Lakes Region) in the U.S. In addition, results are presented to permit evaluation of detection thresholds in relation to sampling effort and levels of risk for Type I errors.

2 Methods

2.1 Field sample protocols

The FIA program conducts a three-phase inventory of forest attributes across the United States (Bechtold and Patterson 2005). The sampling design is based on a tessellation of the United States into hexagons approximately 2,428-ha in size with one permanent plot established in each hexagon. In phase 1 (P1), the population of interest is stratified and plots are assigned to strata to increase the precision of estimates. In phase 2 (P2), tree and site attributes are measured on plots established in the 2,428-ha hexagons. Standing live and dead trees having a diameter at breast-height (dbh) of 12.7 cm and greater are inventoried on four 7.32-m fixed-radius subplots. Within each of the four subplots is a 2.07-m fixed-radius microplot, on which live and dead saplings having dbh of 2.5 cm to 12.6 cm are measured (Forest Service 2005).

During the third phase (P3) of FIA's multi-scale inventory sampling design, DWM data are collected on a 1/16 subsample of P2 plots (Woodall and Monleon 2008). DWM are comprised of two size classes of downed dead wood: coarse and fine woody debris. Coarse woody debris (CWD) pieces are sampled on transects radiating from each subplot center (at angles 30, 150 and 270°, respectively) and have a minimum transect diameter of at least 7.60 cm and a minimum length of 0.91 m. Each subplot has three 7.32 m transects, totaling 87.8 m for a fully forested inventory plot. Information collected for every CWD piece intersected by transects are transect diameter, length, small-end diameter, large-end diameter, decay class, and species. Transect diameter is the diameter of a down woody piece at the point of intersection with a sampling transect. Decay class is a subjective determination of the amount of decay present in an individual log. Fine woody debris (FWD) has a transect diameter less than 7.60 cm and are further divided into three size classes. FWD pieces with transect diameters less than 0.61 cm (small FWD) and 0.62 cm to 2.54 cm (medium FWD) are tallied separately on a 1.83-m slope distance transect (4.27 m to 6.09 m on the 150° transect). FWD with transect diameters of 2.55 cm to 7.59 cm (large FWD) are tallied on a 3.05-m slope-distance transect (4.27 m to 7.32 m on the 150° transect). For details regarding the DWM inventory and associated database please refer to Woodall and Monleon (2008) and Woodall et al. (2010).

2.2 Data

Standing tree data were obtained on forested portions of 8,818 P2 plots in Michigan, Minnesota, and Wisconsin. The first inventory (T1) included the years 2001–2005; the second inventory remeasured plots from T1 and covered 2006–2010 (T2). The biomass of each tree was determined by methods described in Woodall et al. (2011). Merchantable volumes of trees with dbh≥12.7 cm were computed and used to estimate aboveground biomass using published specific-gravity values and estimated tree-component ratios. Biomass of saplings (dbh range 2.5–12.6 cm) was computed from biomass equations and an adjustment factor. The amount of C is then calculated by multiplying by 0.5. The total C for each plot is expanded to a per-unit area basis using the proportion of the plot area that is forested.

DWM (P3) plots established in Michigan, Minnesota, and Wisconsin during 2001–2005 (T1) were visited again in 2006–10 (T2), providing a sample size of 532 remeasured plots. The C density (i.e., Mg/ha) of FWD and CWD was determined through application of estimators detailed in Woodall and Monleon (2008). Briefly, for FWD the volume of FWD is estimated per unit area, and then converted to an estimate of biomass using a bulk density and decay reduction factor based on forest type. An estimate of FWD C is then derived by multiplying the biomass estimate by 0.5. For CWD the volume is determined for every CWD piece then used in an estimator to estimate per unit area volume. Volume is converted into biomass and C through the use of decay reduction factors, bulk density, and C conversion based on a piece's unique species and decay class (Harmon et al. 2008).

2.3 Analysis

The estimation methods described by Van Deusen (2004) for mapped plots were used to compute the estimated means and associated standard errors for C (Mg/ha) contained in standing live, standing dead, and all standing trees (standing live+standing dead) on forest land. Similarly, statistics were also calculated for the C density of medium FWD, large FWD, CWD, and downed dead wood (DWM=medium FWD+large FWD+CWD). Finally, means (and error statistics) for all woody C (standing trees+DWM) were produced. The estimated means were calculated via:

$$\widehat{\mu}_{ik} = \frac{\sum y_{ijk}}{\sum a_{jk}} \tag{1}$$

where:

$\widehat{\mu}_{ik}$ estimated mean (Mg/ha) for woody component i at time k
y_{ijk} observed value for component i on plot j at time k
a_{jk} proportion of plot j that is forested at time k

Estimates of population variance were calculated using

$$\widehat{\sigma}^2_{ik} = \frac{\sum \widehat{e}^2_{jk}}{\sum a_{jk} - 1} \tag{2}$$

where:

$\widehat{\sigma}^2_{ik}$ estimated variance for woody component i at time k

$$\widehat{e}_{jk} = y_{ijk} - a_{jk}\widehat{\mu}_{ik} \tag{3}$$

The estimated standard errors of $\widehat{\mu}_{ik}$ result from $\widehat{\sigma}_{ik}\Big/\sqrt{\sum a_{jk}}$.

Estimates for each of the woody C components were computed at both T1 and T2 and the change over the 5-year period was obtained by subtracting the T1 estimate from the T2 estimate:

$$\Delta\widehat{\mu}_i = \widehat{\mu}_{i2} - \widehat{\mu}_{i1} \tag{4}$$

The estimated population variance of the change in woody component i is

$$\widehat{\sigma}^2_{\Delta i} = \widehat{\sigma}^2_{i2} + \widehat{\sigma}^2_{i1} - 2\widehat{\sigma}_{i12} \tag{5}$$

where: $\widehat{\sigma}_{i12} = \frac{\widehat{e_{j1}}\widehat{e_{j2}}}{\sum a_{j2} - 1}$

The standard error of the estimated change in woody component i, $\Delta\widehat{\mu}_i$, is computed via $\widehat{\sigma}_{\Delta i}\Big/\sqrt{\sum a_{j2}}$. In all cases, the estimated population standard deviation is determined as the square root of the estimated population variance. Note that the sum of the condition proportions, $\sum a_{jk}$, serves as an indicator of sample size. As Van Deusen (2004) notes, this would be equivalent to the number of sample plots (n) if all plots were composed entirely of forest land. To differentiate between number of sample plots and the sum of the condition proportions, the remainder of the paper will use $\widetilde{n}\left(=\sum a_{jk}\right)$ to indicate the sampling effort.

Proper computation of error statistics requires accounting for dependent observations. For the change estimates for each attribute, the same plots were measured at both T1 and T2. Thus, the variance of the change estimates includes the covariance term in the standard equation (5) for the difference between two random variables (Schreuder et al. 2004). A factor that added additional complexity was the combining of standing tree and DWM estimates. In this case, the DWM and standing tree samples were partially dependent, as both attributes were measured on the P3 plots. To account for this fact, the covariance was determined using the method described by Zheng (2004). Using the mean change and associated standard deviation information from each attribute (Table 1), power analyses were conducted at $\alpha=0.05$, 0.10, and 0.20 to examine the relationships between sample sizes and power to detect change in woody C pools. For the all woody carbon evaluation, an effective sample size (the estimated population variance divided by the estimated variance of the mean) was used in the power calculations. In order to determine the power to detect a change from zero, the Type II error rate (β) can be calculated from:

$$\beta = \Pr\left[z < z_{\alpha/2} - \frac{\Delta\widehat{\mu}_i}{\widehat{\sigma}_{\Delta i}\Big/\sqrt{\widetilde{n}}}\right] \tag{6}$$

where:

Pr[·] statistical probability
z random variable having standard normal distribution
$z_{\alpha/2}$ z value for area (standard normal) under curve of $\alpha/2$
others as previously defined

Examination of the above expression reveals that power (1- β) increases as α decreases, $\tilde{n}$ increases, $\Delta\widehat{\mu}_i$ increases, and $\widehat{\sigma}_{\Delta i}$ decreases. Analysts have the ability to control the first

Table 1 Sample statistics for standing and down woody C pools at initial measurement, subsequent measurement, and the change between measurements

Attribute	1st measurement	2nd measurement	Five-year change		
	Mean (Std. err.)	Mean (Std. err.)	Mean (Std. err.)	Percent	Std. dev.
Live tree	42.52 (0.31)	43.77 (0.32)	1.25 (0.13)	2.9	11.29
Dead tree	2.43 (0.04)	2.95 (0.05)	0.52 (0.04)	21.2	3.47
Live/dead tree	44.95 (0.33)	46.72 (0.33)	1.77 (0.13)	3.9	11.44
Med. FWD	0.92 (0.04)	0.65 (0.02)	−0.27 (0.04)	−29.4	0.89
Lg. FWD	2.89 (0.13)	1.58 (0.07)	−1.31 (0.13)	−45.6	2.77
CWD	4.48 (0.24)	4.19 (0.21)	−0.29 (0.16)	−6.4	3.53
DWM	8.29 (0.33)	6.42 (0.24)	−1.87 (0.23)	−22.6	5.01
All	53.24 (0.47)	53.14 (0.42)	−0.10 (0.39)	−0.2	12.58

two factors (particularly α); however, the last two factors are dependent on the sample outcome. The results for this study were obtained using the Power Procedure within SAS statistical software (SAS 2008).

It should be noted that 1) only uncertainty due to sampling is assessed, i.e., other sources of variability such as measurement and model prediction error are not accounted for, and 2) negative estimates of stock changes in this study occur when T2 stocks are less than T1 stocks, suggesting a potential net emission. Given the nature of this study, this accounting notation was used instead of "atmospheric" nomenclature where negative flux estimates suggest net sequestration (i.e., removal from atmosphere).

3 Results

3.1 Standing live and dead tree carbon

Over the 5-year measurement interval, the mean increase in standing live tree C was 1.25 Mg/ha, with a standard error of 0.13 Mg/ha (Table 1). This result represents a 2.9 % increase in C when compared to the T1 mean. The change in standing dead C was 0.52 Mg/ha (standard error of 0.04), which is a 21.2 % increase over 5 years. Evaluation of all standing C provides an estimated mean change of 1.77 Mg/ha, which equates to a 3.9 % increase in all standing tree C stocks.

Using the standard deviation information (Table 1) for each standing tree analysis and a Type I error rate (α) of 0.10, the statistical power to detect the amount of observed change reported above exceed 0.99 in each case. Given the large sample size for monitoring standing tree C, it is not surprising that the magnitude of change indicated in these data were found to be statistically different from zero. Nonetheless, it is instructive to evaluate the power to detect smaller changes under various sample size scenarios. A power of 0.8 (α=0.10) to detect a change in standing live C of 0.7 % is attained using FIA data (Fig. 1a; $\tilde{n}$=7,970). Assuming similar variability to that found in this study, it would be expected that a power of 0.8 (α=0.10) could be achieved for detecting a 1 % change in standing live C using $\tilde{n}$ of 4370 (Fig. 1a). A 2 % change could be detected using $\tilde{n}$ of 1100. Relationships between sample intensity and percent change values at the threshold of power=0.8 for α=0.05 and α=0.20 are also shown for those who may prefer alternative Type I error rates.

Similar analyses at the 0.8 power threshold for standing dead C indicate more difficulty in detecting change than for standing live tree C (Fig. 1b). For the data used in this study ($\tilde{n}$=7,970), a 3.8 % change in standing dead C would be detectable with power=0.8 and α=0.10. Detecting a 5 % change could be accomplished with $\tilde{n}$ of 5050, while a 10 % change would only require $\tilde{n}$ of 1300. Due to the relatively small contribution from standing dead C to all standing C (Table 1), the power curves for all standing C mimic closely those given for standing live C (Fig. 1c). For example, detection of a 1 % change in all standing C at a probability of 0.8 requires $\tilde{n}$ of 4100 (vs. 4370 for standing live C); this suggests only slightly less sampling effort is needed when analyzing all standing C instead of only live standing C.

3.2 Dead down woody carbon

The medium FWD, large FWD, and CWD components of DWM all exhibited negative change estimates (Table 1). The estimated mean change for medium FWD was −0.27 Mg/ha (−29.4 %) with standard error of 0.04 Mg/ha. The change in large FWD was

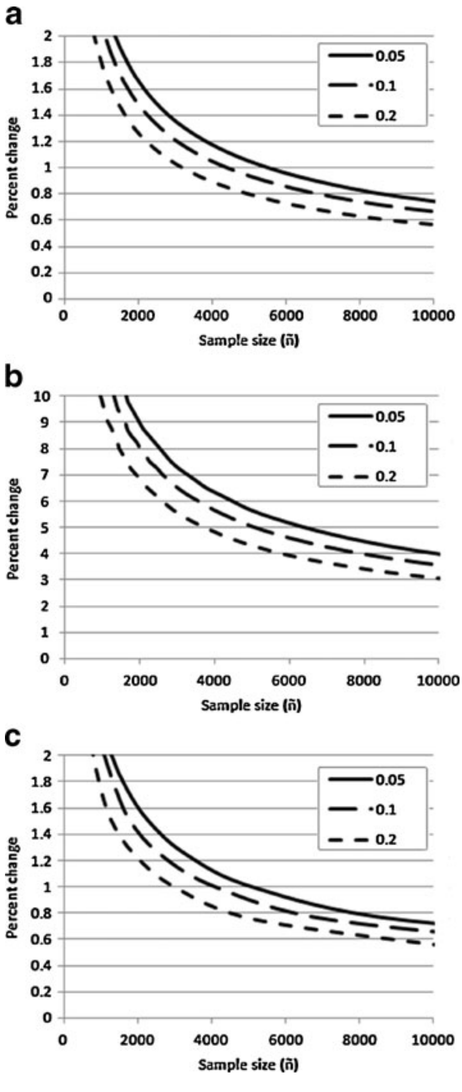


Fig. 1 Sampling effort needed to detect percentage change with statistical power of 0.8 at α=0.05, 0.10, 0.20 for **a** standing live, **b** standing dead, and **c** all standing woody C pools

substantially greater, with −1.31 Mg/ha (standard error of 0.13) being the estimated change over 5 years. Of all the woody C components analyzed, large FWD had the largest change percentage (−45.6). In comparison to FWD components, CWD exhibited a notably smaller percentage change (−6.4); which equates to −0.29 Mg/ha (standard error of 0.16). Combining the three components into a single estimate for DWM resulted in an estimated mean change of −1.87 Mg/ha (standard error of 0.23). This outcome represents an estimated change in down woody C of −22.6 %.

Power analyses (α=0.10) using the standard deviation information (Table 1) and $\tilde{n}$=480 showed the statistical power to detect the observed change statistics reported in Table 1 were greater than 0.99 for medium FWD, large FWD, and total DWM, while the power for CWD was 0.56. With the exception of CWD, the high statistical power arises from the relatively large changes found in these data (in contrast to standing live C where the high power derives from the large sample size). Examination of power/sample size relationships (α=0.10) suggests that changes as small as 5 % in both medium and large FWD could be detected with power of 0.80 if the $\tilde{n}$ was approximately 2300 (Fig. 2a, b). If $\tilde{n}$ of only 300 were available, changes greater than 14 % would be needed to have power of at least 0.80. A smaller sampling effort would be needed to detect a 5 % change in CWD, as $\tilde{n}$ of 1550 would be needed (Fig. 2c). Similarly, $\tilde{n}$ of 200 would be needed to detect a 14 % change. Combining the three components into estimates for DWM C, a 5 % change can be detected with power of 0.80 when $\tilde{n}$ is 900 (Fig. 2d); while $\tilde{n}$ of approximately 120 is sufficient to find differences as large as 14 %. Using the observed data ($\tilde{n}$=480), a 6.9 % change is needed to be detected with power of 0.80.

3.3 Total aboveground woody carbon stocks

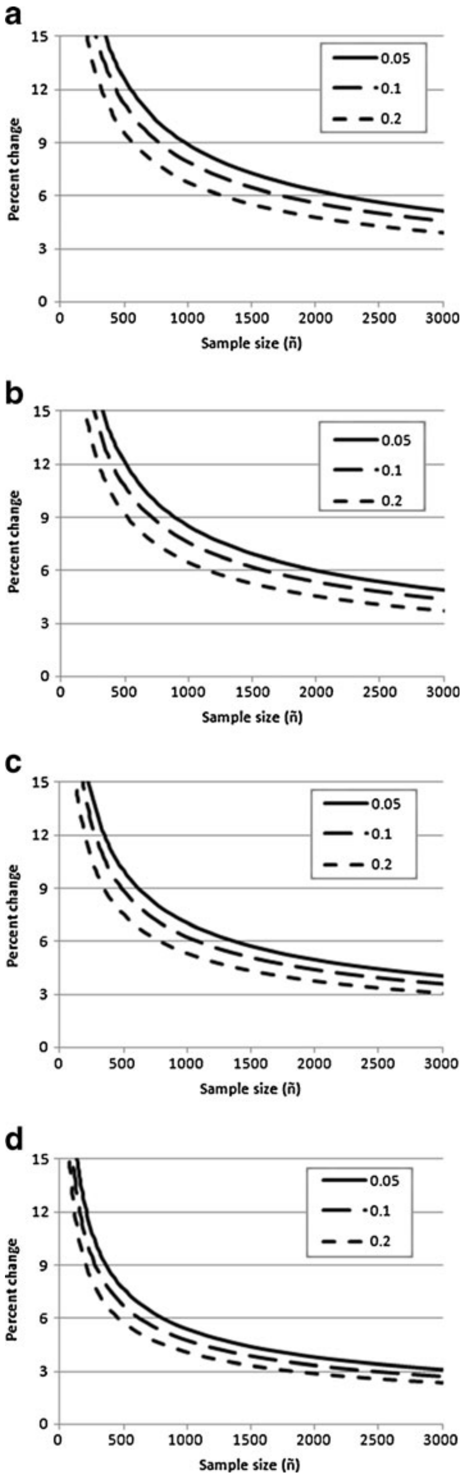
The estimated mean change for all aboveground woody C (live/dead standing and DWM) was −0.10 Mg/ha (−0.2 %) with standard error of 0.39 Mg/ha (Table 1). Power to detect the change in all woody C of −0.10 Mg/ha was 0.11 for α=0.10 and $\tilde{n}$=1,040. To detect change with power of 0.80, a difference of about 1.8 % would need to have occurred (Fig. 3). This result differs substantially from the component analyses where power exceeded 0.99 for all components of woody C except CWD. There were two primary reasons that caused the power to decrease considerably. First, the change in all woody C relative to the pool size was very small. Given that small changes are more difficult to detect statistically, the power is lessened. Second, the standard deviation for change in all woody C was larger than those reported for the other components. The combination of a small change value and high variability has detrimental effects on statistical power.

It is worthwhile to note that this result does not imply the entire forest ecosystem was an emissions source. To make such a determination, other C pools, such as belowground woody C, soil organic C, and forest floor C (duff, litter, etc.), would need to be analyzed as well. However, the result does suggest that aboveground woody carbon may have been a C source rather than a C sink during the time period studied. The maturing forest resource across much of the study area typically has positive net growth (i.e., greater live tree C stocks), albeit at a slower rate than forests composed of younger stands. Increases in downed dead wood stocks are usually only found where stand disturbances occur, e.g., mortality events such as insects or blow downs (Woodall and Nagel 2007). The reduction in downed dead wood C stocks may be attributed to the decay/fracturing of residual pieces with a concomitant lack of major disturbance events.

3.4 Effect of spatial scale and alternative Type I (α) error rates

The quasi-systematic nature of the FIA sample design inherently links sample size to spatial extent. Thus, one can infer how $\tilde{n}$ would change if the spatial scale for analysis was altered. For example, if Michigan contained approximately 50 % of the forest land within this study area, then it would be expected that $\tilde{n}$ for a Michigan analysis only would only be about one-half of the number given for the three-state study area. Anticipating results at regional or national scales is more difficult. Sample sizes will increase proportionally with area; however, it is also likely that increased variability will be encountered. While it is suspected that the increase in sample size will more than compensate for increased variance such that power would increase as larger areas are evaluated, the validity of the assumption remains untested. In the particular case of FIA, national scale assessments are currently not possible due to lack of remeasurement data in many Western states. The results shown should only be

Fig. 2 Sampling effort needed to detect percentage change with statistical power of 0.8 at α=0.05, 0.10, 0.20 for **a** medium FWD, **b** large FWD, **c** CWD, and **d** DWM woody C pools



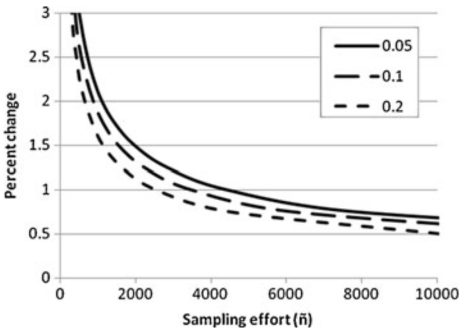


Fig. 3 Sampling effort needed to detect percentage change with statistical power of 0.8 at α=0.05, 0.10, 0.20 for all woody C pool

used to evaluate the power to detect change at spatial scales/locations other than that used in this study if it is reasonable to assume the population standard deviations are similar to those reported here.

Up to this point, the reporting of results has focused on α=0.10 as this is considered to be a reasonable Type I error rate; however analyses were also performed for α=0.05 and α=0.20 (Figs. 1 and 2). Traditionally, α=0.05 is used in research because the emphasis is dogmatically on avoiding Type I errors. If this rate is used when evaluating change values, the sampling effort needed to detect change of a certain magnitude increases by 27 % when compared to α=0.10. Similarly, the sampling effort for α=0.05 increases by 74 % when compared to α=0.20.

4 Discussion

The results provide insight into the sampling effort needed for forest inventory programs that monitor woody C pools. For the changes found in this study, with the exception of CWD and all woody C, the power to detect change was very high. In the case of standing woody C, the large sample size helped maintain statistical power. For DWM, the samples sizes were much smaller, but the magnitudes of changes relative to the pool sizes were quite large with large changes being easier to detect and thus having high power. As such, guidance emerges regarding numerous stock-change scenarios. For example, this study shows that all components of DWM had estimated decreases in C while the standing dead component increased. This suggests that perhaps a considerable input to DWM may be imminent as the standing dead begin to fall. If such circumstances were to occur, both the change in standing dead and DWM C pools would be smaller and the power to detect change would likely diminish. Conversely, disturbance events of various intensity and spatial extent could dramatically alter normal rates of input into woody C pools, transition between woody C pools, and emissions within woody C pools. As estimation of change in the diverse components of woody C pools using large-area forest inventory data in the U.S. has just begun (Woodall 2012), continued monitoring of woody C pools is needed to assess the variability in rates of change over time as well as evaluate the ability to detect C flux resulting from various disturbance events.

An important consideration in these analyses is the relative sampling effort between DWM (P3) and standing tree attributes (P2). The P3 sample is approximately a 1/16 subset of the P2 sample. These disparate sample sizes contribute to decreased power to detect changes in all woody C, as the effective sample size arises from a combination of the P2 and P3 sampling effort. For this study, the effective sample size for all woody C was about 1,040.

If the P3 sample size were increased by a factor of four (25 % of the P2 sample), the power to detect a 1 % change increases from 0.39 to 0.95. Of course, improvements in statistical power would come at a cost. The most obvious would be the additional financial expense of obtaining DWM information on more plots. A more likely cost incursion would be in opportunity, as maintaining field-work efficiency would require elimination of other data elements such that the time to measure a plot remains static. Given the importance of monitoring changes in woody C stocks, increasing the P3 sample size for DWM should be considered.

Type I and Type II errors should be evaluated in the specific context of changes in woody C pools. If a Type I error is committed, the erroneous conclusion is that a change in C of specified magnitude has occurred when it actually has not. Guarding against these misconceptions is accomplished via selection of a low error rate, e.g., $\alpha=0.10$. Also to be avoided is determining that a specified change threshold has not been reached, when in fact the magnitude of change has exceeded the threshold (Type II error). With the exception of the all woody C pool, all change estimates were statistically different from zero at $\alpha=0.10$; with associated power >0.99 (except CWD). As such, there is little concern that either a Type I or Type II error is occurring. However, for all woody C, the change estimate is not statistically different from zero at $\alpha=0.10$; with associated power of 0.11. In this case, Type I error is not an issue as the null hypothesis was not rejected, but the probability of a Type II error is 0.89. Thus it is highly likely that a change in all woody C did occur, but it remained undetected from a statistical standpoint. Traditionally, analysts have focused on minimizing Type I errors and the resultant Type II rates are often ignored. Clearly, if identifying changes in C pools are important, Type II error rates should be afforded more attention. Analysts must decide the magnitude of change that is meaningful to detect from a practical standpoint. An appropriate balance between Type I and Type II error rates requires evaluation of the potential negative consequences associated with each type of error in the context of the hypothesis being tested.

Quantifying changes in woody C pools has recently become an international concern. For instance, the United Nations REDD (Reducing Emissions from Deforestation and Degradation) program has its primary basis in C accounting. The analyses conducted in this study showed that changes (inclusive of possible degradation activities that reduce C stocks) in most woody C pools can be detected using forest inventory data, with the caveat being that sufficient sampling effort is employed to overcome the variability in the population. As such, woody C monitoring systems need to be developed that carefully consider the magnitude of change to be detected that is ecologically meaningful and define the spatial scale for analyses. Failure to consider these factors in the planning process may result in monitoring programs that are unable to detect relatively large losses or gains in woody C pools.

5 Conclusion

Key factors in the efficacy of using forest inventory data to monitor C pools are the level of sampling effort unique to every forest inventory and the desired magnitude of change to be detected. Based on the U.S.'s forest inventory and monitoring aspects used in this study, the observed changes in component C stock density were found to be statistically different from zero; however the estimate of −0.10 Mg/ha for all aboveground woody C could not be shown to be different from zero. This was partially due to the U.S.'s national sample design, which results in large sample size differences between certain pools (standing live vs. downed dead), but the broader implication is that the sample size was not sufficient to detect a change of that size. As sample designs and sampling intensities may be optimized for traditional attributes such as standing tree volume, detection thresholds for various woody C pools may be largely unattainable under the current design and/or highly variable among the different C pools. While the current inventory design and sample intensity in the U.S. may not be able to statistically detect slight changes (<1 %) in forest woody C stocks at sub-national scales, large disturbance events (>3 % stock change) would almost surely be detected.

While multi-tier approaches to forest C accounting offer an array of monitoring techniques, arguably ground-based inventories provide a potentially robust method for monitoring stocks below the canopy (e.g., DWM) with estimators whose properties are generally well understood and widely accepted (i.e., sample-based forest inventory designs). Despite being rooted in empirical forest measurements, the question remains as to whether forest inventories have the statistical power to detect change, especially change in C stocks of DWM at small spatial scales. Under a new paradigm where changes in woody C pools are of increasing importance, modifications or enhancements to existing inventory designs will likely be needed to statistically detect change of specified magnitudes at desired scales of spatial resolution.

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