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Research Article

Assessing Forest Production Using Terrestrial Monitoring Data

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Accurate assessments of forest biomass are becoming an increasingly important aspect of natural resource management. Besides their use in sustainable resource usage decisions, a growing focus on the carbon sequestration potential of forests means that assessment issues are becoming important beyond the forest sector. Broad scale inventories provide much-needed information, but interpretation of growth from successive measurements is not trivial. Even using the same data, various interpretation methods are available. The mission of this paper is to compare the results of fixed-plot inventory designs and angle-count inventories with different interpretation methods. The inventory estimators that we compare are in common use in National Forest Inventories. No method should be described as "right" or "wrong", but users of large-scale inventory data should be aware of the possible errors and biases that may be either compensated for or magnified by their choice of interpretation method. Wherever possible, several interpretation methods should be applied to the same dataset to assess the possibility of error.

1. Introduction

National forest inventories are an expensive and time-consuming operation, particularly in large, remote, and inhospitable regions. There is therefore great interest in alternative measures to estimate forest growth, such as remote sensing [1] or mechanistic process modeling [2]. These methods, however, are not a direct measurement of the same physical characteristics as in an inventory, and it is reasonable to suggest that estimates made with these alternatives should be shown to be unbiased with reference to ground data.

In the near future, national forest inventories will form an integral part of the way that many nations determine their national carbon balance, and inventories are used to estimate forest increment as a means of monitoring their value as a carbon sink. Relatively minor errors in current standing volume estimates may have little practical or policy impact, but these may translate to substantial errors and biases in the estimate of forest increment. In some cases, these biases may mean the difference between forest areas being assessed as a sink or a source of CO_2 or could result in erroneous (but substantial) financial penalties to countries signing up to successor agreements to the Kyoto protocol. Conversely, countries may claim carbon credits for a degree of forest sequestration that does not in fact exist.

Until recently, inventories were conducted solely as a means of measuring the timber resource present in a region, generally in order to determine its immediate extractive capacity. The inventories were optimized to most efficiently estimate a particular forest parameter, current standing volume. This was and still is important, as it describes a crucial aspect of forested landscapes. The carbon sink strength of forests is not, however, directly related to standing volume, but is a function of forest increment. Mathematically, increment is simply the difference in standing volume between two periods, plus the volume of any removals from the growing stock. In practice however this is not so simple, as sample designs or locations may vary between increments, forest area may change and some inventory designs use a nonadditive method of increment estimation (where, at the individual plot level, increment does not equal the difference in standing volumes) [3].

In recent decades, regular forest inventories have been established in many countries using a permanent plot design to reduce the sampling error of the resulting increment calculations [4]. Remeasurement intervals range from 5 to 10 years and either fixed area plots or angle-count sampling [5] may be used. In the latter case, three common methods may be applied to repeated measurements in order to estimate forest increment: the difference, starting value or end-value methods. Upscaling plot-level increments from fixed-plot inventories or using any three of the angle-count estimation methods produces mathematically unbiased estimates of increment [6–8]. It has been shown, however, that measurement error affects the various estimators differently, and thus different estimators will produce different results [6]. It has been suggested that comparing the results of different estimators can indicate the presence of measurement error and thus be used as an inventory auditing tool [6, 9].

In a theoretical simulation study using plausible estimates of measurement errors Eastaugh and Hasenauer [6] reported possible biases in angle count-derived increment estimates of up to ± 0.4–$1.0\,m^3$/ha/yr when averaged over 30 years, depending on the nature of the error and the estimation method used. The key findings of that study were that errors can result in different magnitudes of increment bias and may manifest in the either the period in which the error occurred or in subsequent periods, depending on the increment estimation method used. Thomas and Roesch [9] applied different interpretation methods to large-scale inventory data from the southern United States and found that an up to 48% difference in increment estimation was present between methods, which they attributed to trees being missed (not counted) in the first inventory period. The Eastaugh and Hasenauer [6] study found that a 44.3% increment difference could result from inventories errors that gave rise to an only 4.6% error in volume estimation.

Applying several methods to the same dataset can, however, give substantially different results due to sampling variation, even in the absence of error. The different results are all equally valid estimators, but precision may be poor if relatively few plots are sampled. In such cases, it may be difficult to determine which (if either) of the estimators may be error affected and doubts can be raised over which estimated value should be accepted. Similarly, if inventory data is to be used as a baseline to compare against modeled or remote-sensed estimates of forest characteristics, then it is important to first ensure the integrity of the inventory estimate. This can be done by applying more than one estimation method and ensuring that the final results are within a predetermined range of each other.

In this study, we mimic a large scale forest inventory through simulating 12 000 fixed area and angle count samples inside a large long term forest monitoring plot at Hirschlacke in northern Austria, over 7 measurement periods from 1977 to 2007. We are interested in how such errors may be detectable in mean increment estimates with high variance. Our primary purpose is to confirm the non-biased nature of each of the increment estimators in the absence of measurement error and determine the minimum number of such sample plots necessary to support the concordance of different combinations of estimators.

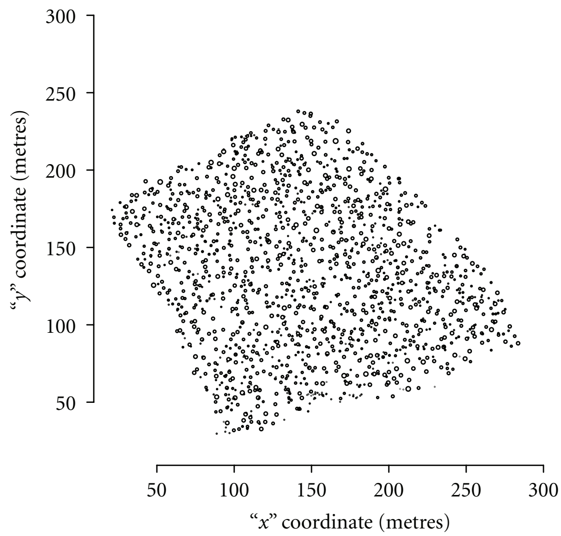

Figure 1: Stand layout at the Hirschlacke long-term forest monitoring plot. Sizes of circles are proportional to diameter at breast height, ranging from 5 to 75 cm. Axis coordinates are in metres.

2. Data and Methods

We obtain data from the 3.47 hectare Hirschlacke long-term forest growth monitoring site in northern Austria [10]. When first measured in 1977, the stand was almost pure 110-year-old Norway spruce (*Picea abies* L. Karst) and has since then been managed under a target diameter harvesting regime [11] designed to produce an equilibrium dbh distribution. All trees of over 5.0 cm dbh have been measured for both diameter and height at five yearly intervals since 1977 and their location coordinates are precisely recorded. Figure 1 depicts the stand layout in 1977.

Since 1977, the stand structure has changed from having 1510 trees with a mean dbh of 34.6 cm (standard deviation 14.3 cm) to 2820 trees with mean dbh 18.2 cm and standard deviation 17.5 cm in 2007. Mean tree heights have followed a similar pattern, from 25.8 m (standard deviation 8.9 m) in 1977 to 14.8 m (standard deviation 12.7 m) in 2007. This has been achieved by the removal of an average of $74\,m^3$ of timber in each inventory period (timber volumes calculated according to the allometrics of Pollanschütz [12]). Under this permanent-cover management system, the standing volume on the site remains relatively constant over time, although diameter distribution is currently quite different to that in 1977, providing a diverse sampling space across time.

We use the Hirschlacke dataset as a means of mimicking a large-scale national inventory. As all trees in the plot are repeatedly remeasured, we are able to simulate what increments would be determined using angle counts or small fixed-area sample plots assuming perfect measurements and also with a range of simulated error conditions. The dataset is thus an ideal means of demonstrating the potential biases that may be apparent in angle-count-based inventories containing error [6], or in this study, comparing the results of different increment estimation methods.

We construct a pattern of 12 000 points at a 1×1 meter spacing within the Hirschlacke plot, such that no point is within 30 meters of the plot boundary. We then simulate a fixed area plot of 200 m^2 and an angle-count sample with a basal area factor of 4 at each point in each of the seven measurement periods. This mimics the plot size used as part of the Swiss National Forest Inventory [13] and the basal area factor used in Austria [14].

Increments are estimated four ways.

(1) Differences between time 1 and time 2 volumes determined from fixed-area plots, plus removals (fixed-plot method).

(2) Differences between time 1 and time 2 volumes determined from angle-count plots, plus removals (difference method).

(3) The recorded increment of the trees within the angle-count sample multiplied by the estimated number of trees of that size in the stand in time 1, plus the volume of the new trees entering the stand. (starting value method).

(4) The recorded increment of the trees within the angle-count sample multiplied by the estimated number of trees of that size in the stand in time 2. (end value method). This method requires the estimation of prior dimensions of trees which (in a practical inventory situation) may not have been recorded at time 1.

Much of the published literature on deriving increments from angle-count sampling distinguishes between "survivors", "ingrowth", "ongrowth", and "nongrowth" trees (cf. Martin 1982 [15]), depending on whether they were above or below a particular diameter at breast height in the period preceding the current measuring period and whether they were counted "in" or "out" of the angle count in the preceding period (Table 1).

Defining the following variables.

Z = volume increment per hectare, with superscripts F for fixed are plots, D for difference method, S for starting value method, and E for end value method;

m = Number of sample plots;

n_j = Number of trees in each sample j;

v_i = volume of individual tree i;

a_j = area of fixed area plot j;

K = basal area factor;

g_i = basal area of individual tree i. and denoting measurements made in a subsequent inventory period by $(*)$, ignoring tree removals from the plots and following Hradetzky (1995) [16] and Eastaugh and Hasenauer [6], the mathematical form of the four methods may be presented as:

$$Z^F = \frac{10000}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}^*}{a_j} - \frac{10000}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}}{a_j}, \tag{1}$$

$$Z^D = \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}^*}{g_{ji}^*} - \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}}{g_{ji}} + \frac{K}{m} \sum_{j=1}^{m} \sum_{i=n+1}^{n_{ji}^*} \frac{v_{ji}^*}{g_{ji}^*}, \tag{2}$$

$$Z^S = \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}^*}{g_{ji}} - \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}}{g_{ji}} + \frac{K}{m} \sum_{j=1}^{m} \sum_{i=n_j+1}^{n_j^*, g_{ji}<19.63_i} \frac{v_{ji}^*}{g_{ji}^*}, \tag{3}$$

$$Z^E = \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}^*}{g_{ji}^*} - \frac{K}{m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} \frac{v_{ji}}{g_{ji}^*} + \frac{K}{m} \sum_{j=1}^{m} \sum_{i=n_j+1}^{n_j^*} \frac{v_{ji}^*}{g_{ji}^*} - \frac{K}{m} \sum_{j=1}^{m} \sum_{i=n_j+1}^{n_j^*} \frac{v_{ji}}{g_{ji}^*}. \tag{4}$$

The term $\sum_{i=n_j+1}^{n_j^*}$ in (2) and (4) describes the "new" trees entering a sample in the subsequent measurement period and includes nongrowth, ongrowth, and ingrowth. In this formulation of the difference and end value methods, the three types of new tree need not be distinguished. The starting value method does not include nongrowth, so only those new trees with a previous dbh of less than 5.0 cm (basal area less than 19.63 cm^2) are included in (3).

Mean per hectare volume and increment estimates (without errors) for each plot across each and all time periods are compared with paired t-tests. In these examples, we use 84 000 paired data points for volume calculations and 72 000 for increment, thus even very small differences may be deemed to be statistically "significant". In practical applications, however, given the large variances in increment estimation, the null hypothesis (that the means are the same) is difficult to reject even if the mean values appear quite different. If differences due to measurement errors were present, we are interested to determine a minimum number of samples necessary to detect that difference. To do this, we estimate the population mean increment and standard deviation through lumping data from all periods and applying standard statistical procedures [17] to find the minimum number of paired samples that will give a t-test with 90% confidence that the means are within 5%, with 95% power.

$$n = \frac{s_d^2}{\delta^2} \left(t_{\alpha(2),\nu} + t_{\beta(1),\nu} \right)^2, \tag{5}$$

where: n= required minimum sample size, s_d^2 = variance of the differences, δ = maximum allowable error, $t_{\alpha(2),\nu}$ = t statistic at significance α, two tailed, and degrees of freedom ν, $t_{\beta(1),\nu}$ = t statistic for power 1-β, one tailed, and degrees of freedom ν.

These minimum sample sizes are then tested by drawing that many random plots from the data and comparing the appropriate increment estimators with a paired t-test. This is repeated 1000 times, and we report the number of times where a statistically significant difference of greater than 5%

Table 1: Components of growth in angle-count sampling.

Tree classification	dbh in measurement period 1	dbh in measurement period 2	Presence in Angle-count sample, period 1	Presence in Angle-count sample, period 2
Survivors	>threshold	>threshold	IN	IN
Ingrowth	<threshold	>threshold	IN	IN
Ongrowth	<threshold	>threshold	OUT	IN
Nongrowth	>threshold	>threshold	OUT	IN

appears to be present. These routines are implemented in the "sample size" package in the "R" programming environment [18]. Users of this package should note that it assumes one-sided tests, thus the value of α must be adapted to the two-tailed equivalent.

3. Results

3.1. Standing Volume and Volume Increment. The mean volume estimated across all plots and time periods using fixed area methods was 775.5 m^2/ha, with a standard deviation of 244.8 m^2/ha. Using angle counting, the mean was estimated as 779.8 m^2/ha, with a standard deviation of 168.2 m^2/ha. The difference of 0.55% of mean volume is statistically significant at 95%, $P = 3*10^{-5}$. This statistical significance is a result of the very large number of data points (Figure 2). A breakdown of volumes estimated in each period is given in Table 2. The mean increment estimated across all plots and time periods with the four available estimation methods is given in Table 3. All differences were significant at $P < .001$.

3.2. Minimum Number of Plots Required to Detect Differences. The procedure for determining the minimum number of plots needed depends on the variance of the differences between the two methods to be compared, as per (5). This is given in the lower left portion of Table 4. The upper right portion of Table 4 gives the minimum number of plots required to detect a 5% difference in increment estimates using different methods at 90% confidence, with 95% power in a paired t-test. Randomly selecting these numbers of plots from the dataset and comparing increment estimates with a t-test shows that in less than 0.1 percent of 1000 repetitions a spurious difference of greater than 5% is found between the estimates (bracketed values, Table 4).

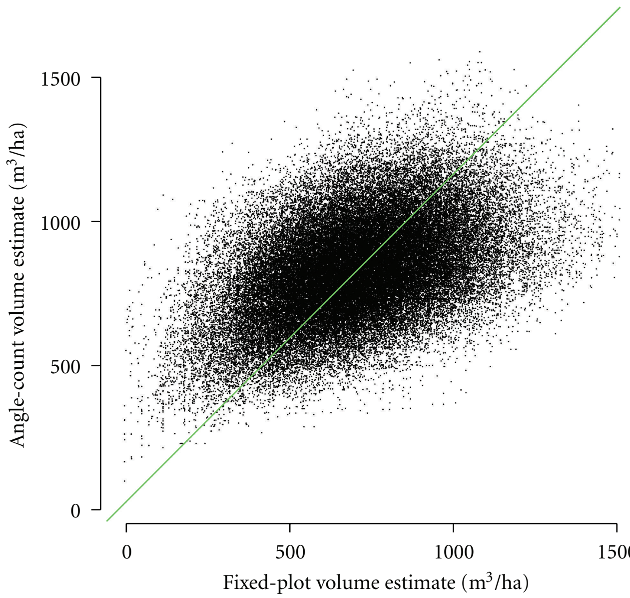

Figure 2: Comparison of fixed area and angle-count estimates of stand volume. Each point represents the sample measurement at each of the 12 000 simulated sample plots in one of the seven measurement years (84 000 data points).

4. Discussion

The data we amass from the Hirschlacke stand provides us with 12 000 simulated plots over 7 years, which ranged from zero to 1800 m^3/ha (Figure 2). The size and spread of this dataset is comparable to that of the Austrian National Forest Inventory, comprising 9182 plots containing trees in the 2007–2009 period with angle-count volume estimates ranging from 1 to 1806 m^3/ha, with a mean of 344 m^3/ha and a standard deviation of 241.5 m^3/ha (Eastaugh, unpublished data). Even though a plot of only 3.47 ha cannot of course represent the variability across the whole forest estate, Figure 2 shows how much variation can be found between plots even in such a small area. Examination of Table 2 shows that although the means are substantially different, the variation around the mean in our simulation is comparable to that from the real NFI. This suggests that a substantial portion of the variability in an inventory is due to the fine-scale estimation variability between plots, even plots within the same stand, rather than to the true broad-scale differences between forest stands in different areas. The synthetic dataset that we construct mimics an NFI and allows the exploration of theoretical aspects of inventory sampling without the added complications of measurement error issues.

It is important to recognize that the dataset we construct is a hypothetical forest inventory and is not validly comparable with any comprehensive calculations of volume or increment from the Hirschlacke stand. A valid sampling design would require that all points in the stand have an equal possibility of sampling. Although in theory, it

Table 2: Comparison of fixed-area and angle-count estimates of stand volume, for the 12 000 plots simulated in each measurement year.

Measurement year	Fixed-area volume estimate		Angle-count volume estimate	
	Mean (m^3/ha)	Std. dev.	Mean (m^3/ha)	Std. dev.
1977	759.0	231.3	762.5	172.4
1982	769.3	226.3	774.6	161.9
1987	772.7	225.3	775.2	155.1
1992	818.2	241.2	822.4	163.9
1997	798.6	242.5	806.0	158.7
2002	775.5	259.0	780.8	168.0
2007	735.3	275.5	737.1	181.9

Table 3: Comparison of fixed-area and angle-count estimates of stand increment per 5 years, for the 72 000 data points simulated in each measurement year.

Method	Increment estimate, m^3/ha/5 years	
	Mean	Std. dev.
Fixed-area plots	67.88	28.14
Angle counts, difference method	69.01	56.97
Angle counts, starting Value method	68.23	21.89
Angle counts, end Value method	68.24	21.13

would be possible to extend our sample grid to encompass the whole stand, problems then arise with the boundary overlap problem, where some sample plots extend to outside the stand. Solutions to this may exist [19] but would be computationally extremely expensive to institute in our simulation. Our purpose in this paper, however, is not to assess the accuracy of each inventory method in estimating the values of a true stand, but to compare the estimates made with different methods from the same set of points.

The apparent statistical significant differences in volume results from different methods arise from the large number of plots. However, at 0.55% of volume and a maximum of 1.66% of increment, these differences are not functionally significant [20]. This difference does not arise in a properly conducted inventory, as both fixed-area plots and angle-count plots are unbiased sampling procedures. In this respect, our hypothetical inventory may slightly flawed, as we effectively sample from a forest stand without edges and the population sampled with angle counts is slightly different to that sampled with fixed-area plots, even though both use the same plot centres. Nevertheless, significance testing with sufficiently large samples will always find “some” significant difference, even if the null hypothesis that the sample means are equal is actually true [21]. Given that the effect size is so small, we believe that this difference does not invalidate our sample collection for the purposes of this paper. Moreover, the (hypothetical) populations sampled for analysis with the three angle-count-based increment estimators are identical and thus validly comparable.

A single fixed-plot will measure different trees to an angle count with the same centre and thus high variance in the difference between each individual plot is to be expected. Interestingly, the behaviour at the extremes appears to be quite different, as the fixed plot estimates appear to give higher values than the angle counts in denser portions of the forest bur lower values in regions with lower density (Figure 2).

The difference method of increment estimation has very high variance in itself (ref. Table 3), as it is dependent mostly on how many new trees (either ingrowth, ongrowth or nongrowth) enter a sample in a remeasurement period. Multimethod estimation comparisons involving either of these two methods will thus require a large number of plots (Table 4). When comparing the starting value and end value methods, most trees that make up the increment estimate are the same trees, the only difference in the sample is due to the nongrowth trees that enter the sample in the remeasurement. This explains the plotwise intermethod variance of only 7.39 m^3/ha/5 years. It is important, however, to note that the end value method requires knowing or estimating the dimensions of nongrowth trees in the period prior to when they entered the sample. In our example studied here this information was known from the long-term monitoring records, but in real inventories it is usually estimated with regression equations. This may change the variance in the estimates in comparison with other methods. The inclusion of nongrowth trees enlarges the sample and so in principle the estimate should be more precise. This effect is, however, lessened by the fact that the covariance is greater as the survivor estimates are calculated using their inclusion probabilities at time 2, when the basal areas are larger [16]. Hradetzky [16] derived equations showing that increments derived from the end value method would have “slightly” less variance than the starting value method, if prior tree dimensions were known. Roesch et al. [22] and Heikkinen and Henttonen [23] however give details of empirical studies showing that the standing volume at the time of first measurement can be substantially more precisely estimated

Table 4: Minimum number of plots required to detect a 5% difference in increment estimates using different methods at 90% confidence, with 95% power in a paired t-test. Numbers in italics are the standard deviation of the differences between each pair of methods, numbers in normal text are the required numbers of plots. Values in brackets are the number of times that a t-test using the appropriate number of plots (randomly selected) incorrectly suggested that a significant difference of greater than 5% existed, from 1000 iterations.

Method	Fixed plot	Difference	Starting value	End value
Fixed plot	—	3204 (8)	491 (2)	490 (2)
Difference	*59.34*	—	3032 (4)	2416 (6)
Starting value	*23.19*	*57.72*	—	52 (2)
End value	*23.17*	*51.53*	*7.39*	—

by regressing information available only at time two. Our results in Table 2 (with perfectly known tree volumes prior to their first-angle-count measurement) support Hradetzky's view, leading to the conclusion that a modeled estimate of time one volume made with an angle count from a particular point may in fact be more precise than the actual observation made from that point. To the best of our knowledge, this artificial reduction in sampling variability has not yet been formally justified from a conceptual standpoint. At issue is which sampling method best represents the true variability of the stand, which would first require defining stand variability at a scale compatible with the scale-indeterminate samples. This, we suggest, is a problem for another day.

In real inventory situations, both fixed-area estimates and angle counts are not likely to be available for the same region in one-time period. If our comparisons of increment estimation here are to be applied to National Forest Inventories, then this will be limited to those inventories based on angle counting (i.e., Finland, Germany, and Austria).

All efforts at assessing large-scale ecosystem productivity will be estimates, whether they depend on "top down" approaches from satellite data [24] or use "bottom up" methods from terrestrial samples (inventories). Although advances have been made in linking these two approaches [25, 26], success will depend on having a clear understanding of the variability, biases, and limitations of each method. As shown in this paper, confidence in the concordance of estimates derived with different calculation methods is largely an issue of scale.

5. Conclusions

Forest inventories are measured data and thus other forest growth estimation methods such as remote sensing or modeling must be shown to be consistent with accurate inventories in order to claim to represent reality. Inventories, however, are not a full measurement of the whole forest but are an estimate, a statistical model. We have shown here that different inventory interpretation methods can give different results, even though all are mathematically unbiased. If sufficiently large numbers of samples are available then all methods can be shown to agree, but with less than this number, a range of equally plausible estimates could be made.

It is inevitable that any forest measurement program will contain some degree of error, hopefully (but not certainly) small. These errors have different effects on increment estimation, depending on what inventory interpretation methods are used. If two different methods are applied to the same dataset, over a sufficient number of samples, then the integrity of the inventory can be proven. In the case of National Forest Inventories based on angle-count sampling, the procedures in this paper can be easily applied and should be a precondition of using inventory data to validate other approaches to forest-growth estimation.

Appendix

It has been suggested that the slight difference between the volume estimates made with fixed-area plots or angle-count samples may be due to differences in stand density towards the edges of the plot. The fixed area plots are limited to trees within a radius of 7.98 metres of the plot centres, but an angle count will count trees further away than this if they are over 28.2 cm dbh. As the angle count method in our example gave results a little higher than the fixed area plots, this initially seems to imply that the density of the forest in the zone just outside the limitations of the fixed area plots must be higher and that this could easily be tested with our available data. However, the edges of our edges of our study area were found to be less dense than the inner parts. The explanation for the slightly higher volume estimates with angle-count sample plots becomes evident from the following example.

Consider a stand of 4 trees, each of dbh 56.4 cm, in an area of 625 m^2 (Figure 3(a)). A fixed-area plot of radius 14.1 m and an angle-count plot of BAF = 4 m^2/ha are established in the centre of the stand. The true stand density is 16 m^2/ha, and both the fixed area plot and the angle count will arrive at the same conclusion.

If our stand was in fact a little larger (Figure 3(b)), it might include one larger tree of dbh 80 cm and 2 small trees of dbh 10 cm. Assuming a radius of 18 m, the total stand area is now 1017 m^2. The angle count detects the larger tree, and so the density estimate is 20 m^2/ha. The fixed-area plot estimate is the same 16 m^2 as before, but the true stand density is 14.9 m^2/ha, with 16 m^2/ha in the "inner" zone and 13.2 m^2/ha in the outer boundary zone. Even though the outer zone is less dense than the inner and the angle count "sees" further, the angle count appears to result in higher basal area estimate than a fixed area plot with the same centre point.

The differences in volume estimates in the body of this paper do not arise from differences in stand density in different zones of the forest, but are a result of the fact that the

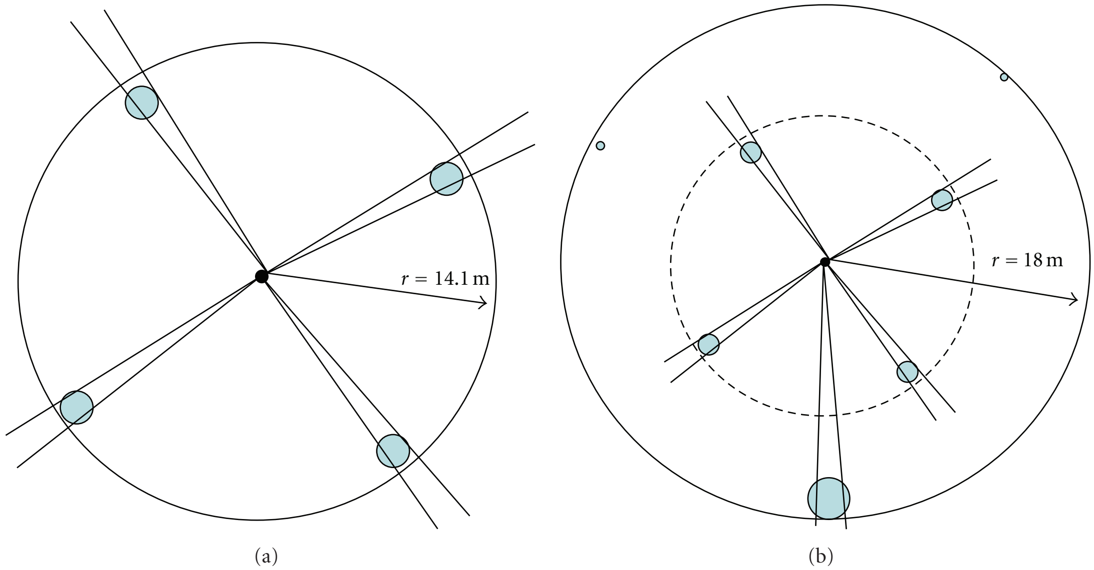

FIGURE 3: (a) Four trees each of basal area 2500 cm^2 in an area of 625 m^2. A fixed-area plot of 625 m^2 or an angle count with BAF = 4 will agree that the stand density is 16 m^2/ha. (b) A stand of 1018 m^2, including the same four trees as (a) plus one tree of basal area 5027 cm^2 and two of 78.5 cm^2 each. The true stand density is now 14.9 m^2/ha, but the fixed-area plot sees 16 m^2/ha and the angle count 20 m^2/ha.

precise area being sampled has not been defined. It would be possible to obtain equal results from each sampling method in our small example in this appendix if we adhered to the following strictures.

(i) The area to be sampled must be strictly defined in space.

(ii) A very large number of plots must be used and aggregated.

(iii) Plot locations must be random, with any point in the defined area having an equal or known probability of selection (including near the edges).

(iv) Estimates from plots where the plot boundary (or the tree's inclusion zone) overlaps the edge of the sampling area must be appropriately adjusted. For angle counts, this is not yet a fully solved problem [19].

For perfect mathematical precision, future simulation studies will need to either develop new, computationally efficient methods to deal with the boundary overlap problem or project their simulated forest onto a sphere thus eliminating boundaries. The purpose of this current paper, however, was to compare collections of point samples, not to assess their accuracy in estimating stand densities in any defined area.

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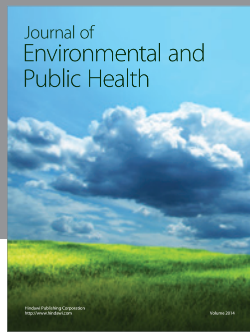

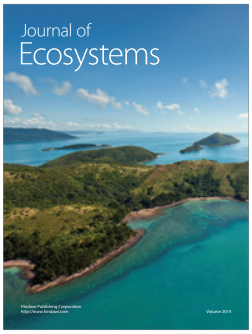

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