



Structure area curves in Eastern Hardwoods: implications for minimum plot sizes to capture spatially explicit structure indices

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Received: 25 August 2020 / Accepted: 19 January 2021 / Published online: 18 February 2021
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Abstract

• **Key message** Sampling needs differ by forest type for timber inventory and structural complexity metrics. We demonstrate in a typical mixed Eastern Hardwoods forest that optimal sampling of timber inventory metrics and spatially explicit structure indices may be achieved in one large plot plus a cruise for large diameter trees, but accurately capturing inventory metrics may not be possible with sparse large-scale sampling.

• **Context** Managing forest stand structures for multiple objectives require accurate and precise estimates of structural features that may be best estimated at different scales.

• **Aims** We document minimum necessary plot sizes for structural metrics and spatially explicit indices to characterize structure in a mature North American Eastern hardwoods forest.

• **Methods** Metrics and indices (Index of Aggregation, Diameter Differentiation Index, Dissimilarity Coefficient, Structural Complexity Index) were calculated within 0.05–1.75-ha plots for 1000 iterations of random placement in two 2.0-ha macroplots. Estimation adequacy required (1) precision (varied < 10% among plots) and (2) accuracy (within 10% of the 2.0-ha value at 5th and 95th percentiles).

• **Results** Minimum single plot sizes to achieve estimation adequacy were 0.25–0.75 ha for spatially explicit indices and 0.5–2 ha for stand metrics. A minimum of five 0.10-ha subplots would be needed for most indices and 6–25 for most metrics, but an untenable 375+ for the density of large diameter trees.

• **Conclusion** Estimation adequacy for structural complexity requires no greater sampling intensity than for timber metrics, except for density of large trees. A single large plot may be most cost-effective. National inventories in Eastern hardwoods may not estimate structural complexity well due to inadequate sampling intensity.

Keywords Sampling · Rarity · Estimation error · Oak · Quercus · Structural complexity

Handling Editor: Andreas Bolte

Contributions of the co-authors Eric Zenner: Conceptualization

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1 Introduction

The objective of forest inventory is optimized parameter estimation: accurately characterizing the population of interest while minimizing the resources required to do so. Consequently, there is a long history of optimizing plot sizes, shapes, and layouts to ensure a swift and adequately realistic assessment of the timber parameters (e.g., density, basal area) that inform stocking charts (Bormann 1953; Freese 1967; Zeide 1980; Kenkel and Podani 1991; Avery and Burkhart 2001). Recognizing the importance of incorporating local variability into the optimal design of a sampling scheme (Bormann 1953; Reich and Arvanitis 1992; Avery and Burkhart 2001), most inventory protocols for timber resources employ relatively large numbers of small, widely distributed sampling plots (e.g., Forest Inventory and Analysis (FIA),

Gormanson et al. 2018). The efficiency of small, often variable radius, plots for characterizing traditional timber metrics persists across forest types and management histories (Berrill and O'Hara 2012; Du et al. 2018).

Management objectives, however, have evolved, and with them the parameters of interest to inventory on both managed lands and strict reserves. As interest in the complex stand structures integral to biodiversity has grown (Crow et al. 2002; Larson 2007), existing inventory protocols have struggled to keep pace. Although the data from inventories based on many small plots can be used to plot diameter distributions and summarize tree species richness and the density of large diameter trees (e.g., Brown et al. 1997; Crow et al. 2002), both theory and practice indicate that special features often have population characteristics that differ from those of density and tree diameter (Kenkel and Podini 1991). The inherent variability of some features (Franklin and Van Pelt 2004; Spies 2004) often dictates more intensive sampling effort to achieve robust estimates (Nagel et al. 2007; Zenner and Peck 2009; Král et al. 2010). Further, while many traditional metrics correlate well between field measurements and remotely sensed (e.g., LiDAR-derived) estimates, predictive models based on remotely obtained textural data are still often inadequate for structural features such as the density of large diameter trees (Kane et al. 2010) or variation in tree size (Mura et al. 2015; Meng et al. 2016), and poorer than expected (Kekunda et al. 2019) or even demonstrably poor for metrics incorporating spatial arrangement (unless additionally drawing on more costly spectral data; Meng et al. 2016; Kandare 2017).

Because the spatial distribution of features within a stand determines their probability of inclusion in a sampling frame, influencing statistic power, field inventory protocols using many small plots are challenged by the incorporation of structural features typical of older, unmanaged forests, which are highly variable in frequency, abundance, and spatial arrangement (Spies and Franklin 1991; Reich and Aravanitis 1992; Gray 2003). Features that are rare and/or unevenly distributed on the landscape (e.g., large trees) are analogous to rare species, which are better captured in fewer large plots than in more small plots (McCune and Lesica 1992). Traditional protocols can be expanded by tacking on larger supplementary plots (e.g., lichen survey plots, FIA, Gormanson et al. 2018), but the root causes of this bias—the influence of spatial pattern on variability—is largely unaddressed when field protocols prioritize the number of parameters over spatial extent and resolution (Proulx 2007).

Choosing an optimal spatial extent (i.e., plot size), however, is itself challenged by the continuous—and nearly functional (cf. Král et al. 2010)—decrease in variation of most metrics with increasing plot size (Busing and White 1993; Zenner 2005; Zenner and Peck 2009; Berrill and O'Hara 2012; Guillemette et al. 2012; Zenner et al. 2015, 2019; Lombardi et al. 2015; Du et al. 2018; Kekunda et al. 2019). In an effect very like the flattening of the species

area curve with sampling effort, which can be captured by plotting “structure area curves” of variation against spatial scale (Zenner 2005), parameter estimation for spatially non-random features often requires larger plot sizes (Kenkel and Podini 1991), especially as forest heterogeneity increases (Kekunda et al. 2019). As spatial extent increases and plots increasingly incorporate diverse features by absorbing multiple patches (Zenner et al. 2019), within-plot variance increases at the expense of between-plot variance (Scott 1998). The heterogeneity evident at small scales is averaged across at larger scales; the resulting homogenization at large scales, known as spatial smoothing (e.g., Zenner and Peck 2018), renders only small gains in estimation efficiency with the addition of more large plots (Kenkel and Podani 1991).

Thus, the need to efficiently incorporate structural features with variable spatial patterns apparently dictates sampling protocols using fewer, larger plot sizes. Further, because plot size influences the assessment of spatial pattern (Zenner and Peck 2009; Fonton et al. 2011; Carrer et al. 2018), the recognition of spatial pattern as a parameter in and of itself (e.g., Aldrich et al. 2003) has different sampling requirements from traditional inventory parameters (Kenkel and Podani 1991). Yet there remains no consensus on a minimum standard plot size for inventorying spatially dependent structural features, even within forest type, because virtually no information is available on the structure area curves of most spatially explicit indices of structural complexity (but see Maleki and Kiviste 2015; Kekunda et al. 2019). Although 1.0-ha sample plots are no longer uncommon when structural features are of interest (e.g., Guillemette et al. 2012; Lombardi et al. 2015; Grotti et al. 2019; Kekunda et al. 2019; Zenner et al. 2019), most inventory protocols continue to use relatively small fixed or variable radius plots (e.g., McGee et al. 1999; Crow et al. 2002; Gormanson et al. 2018), and only a minority of national inventory programs quantify spatially explicit structural features (Winter et al. 2008). As land managers look toward revising these protocols to incorporate structural features, the question remains as to how large a plot is necessary.

The objectives of the current study, therefore, were to (i) derive a structure area curve for a mature Eastern hardwoods forest and (ii) determine the minimum acceptable single large plot size and/or small (0.1 ha) plot sample sizes necessary to estimate structural parameters, including spatially explicit indices, with adequate precision and accuracy.

2 Material and methods

2.1 Sampling

Two adjacent stands (RS1, SV3) were sampled within a typical Eastern hardwoods forest (Fig. 1) on Penn State Stone Valley Forest in central Pennsylvania, USA (40°

37° 37′–54″ N, 77° 54′ 5–9″ W). The stands are on well-drained channery loam soils, classified as medium sites with even-aged stratified mixed hardwoods dominated by oak (*Quercus*) and maple (*Acer*) with a component of white pine (*Pinus strobus* L.). Both stands originated naturally following clearcutting ca. 1920, received minor improvement cuts mid-century, and had been unmanaged since at least 1985.

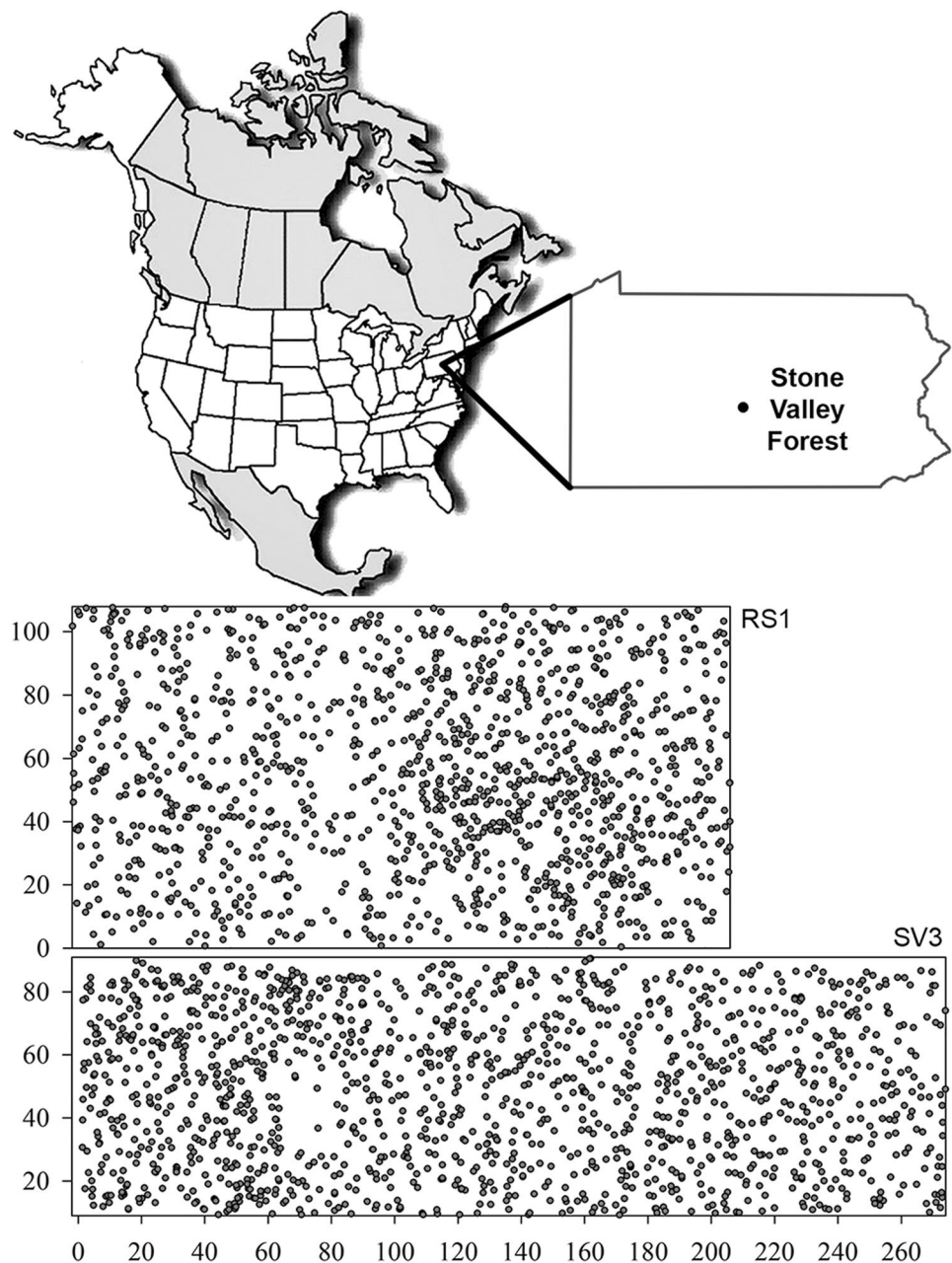
Each stand was sampled using a ca. 2.25-ha macroplot (82 × 276 m and 108 × 208 m, respectively) in the summer of 2007, each shaped to best capture the individual stand. In each macroplot, the position of all live trees ≥ 5 cm in diameter at breast height (DBH) was stem-mapped and

slope-corrected distances and azimuths were converted to Cartesian coordinates. For each tree, species and DBH were recorded (Peck and Zenner 2021). Both macroplots exhibited a reverse-J diameter distribution.

2.2 Parameters

Structure area curves for each macroplot were derived by calculating each parameter at several different scales within each macroplot by overlaying plots of 500, 1000, 2500, 5000, 7500, 10,000, 12,500, 15,000, and 17,500 m² onto each stem map. Plot shapes were kept identical to the 2-ha macroplot core (i.e., rectangular), but rescaled to 0.05 to

Fig. 1 A typical mature even-aged stratified mixed eastern hardwood forest at the Stone Valley Forest in central Pennsylvania in North America (40° 37′ 37–54″ N, 77° 54′ 5–9″ W) was sampled using two differently shaped 2.25-ha macroplots. All trees over 5-cm diameter at breast height (circles) were stem-mapped in each macroplot



1.75 ha in size. We simulated “sampling” by randomly placing 1000 of these variously sized plots within each macroplot. To ensure consistency across plot size/scale, 1000 $[X,Y]$ coordinate positions were randomly selected in each 2-ha macroplot core and then used as the plot centre for sampling at each spatial scale. Torroidal edge correction was used to ensure equal sample probability of all trees while correcting for edge effects (Griffith 1983; Boots and Getis 1988; Gray 2003). This adjustment joins the opposite ends of a mapped area, creating a continuous surface for random plot placement throughout the mapped area (Gray 2003).

The structure parameters assessed in each plot at each scale included five simple metrics (the mean and standard deviation (STD) of DBH (cm), basal area (m^2/ha), tree density (trees/ha), and density of large trees ($\text{DBH} \geq 50$ cm) (large trees/ha)) and six spatially explicit structure indices (see Zenner et al. 2015 for formulas). The index of aggregation (R , Clark and Evans 1954) was used to capture horizontal structure, ranging from 0 (maximum aggregation/clustering of trees) to 2.1491 (a regular hexagonal arrangement) with a value of 1 when the spatial distribution is random. The dissimilarity coefficient (DC) of Hagner and Nyquist (1998) was used to quantify vertical structure as size differences among pairs of neighboring trees, ranging from 0 to 1 with a value of 0.5 when tree sizes are drawn independently from an exponential distribution. Vertical structure was also measured as the difference in tree size among four nearest neighbors (T , the diameter differentiation index of Fuldner 1995, ranging from 0 to 1). Indices were also calculated based on neighborhoods identified after connecting trees to form a triangular surface that, when extended across the entire sampling area, forms a triangulated irregular network (TIN) of non-overlapping triangles (Fraser and van den Driessche 1972). The average difference in tree sizes within these three-tree triangles ($DBHdiff3$), which was also reported scaled from 0 to 1 ($Dd3$), was also used to quantify vertical structure. Finally, both vertical and horizontal structures were assessed using the structural complexity index (SCI ; Zenner and Hibbs 2000), in which trees are represented as irregularly spaced three-dimensional data points ($x, y =$ spatial coordinates, $z =$ tree DBH). The SCI was calculated as the sum of the surface areas of the TINs for a plot divided by the projected ground area of all triangles in the plot.

2.3 Estimation

The mean across the 1000 simulated samples was used as an unbiased measure of central tendency for each parameter

(except R ; see below) at each scale. The estimation error (i.e., bias) for each parameter at each scale was presented as the relative deviation of the simulated sample estimate (i.e., the mean across the 1000 iterations at each scale) from the “true” value, defined as the known value for the 2-ha reference macroplot core (Table 1):

$$rel_dev_j = \frac{\text{abs}(x_{ij} - \mu_j)}{\mu_j}, \quad (1)$$

where x_{ij} is the value of the parameter from a plot of size i in macroplot j and μ_j is the 2-ha value in macroplot j (after Gray 2003).

The mean and the 5th and 95th percentiles of the distribution of the estimation error were calculated for the 1000 simulated plots of each parameter in each macroplot. Variation among scales, and therefore adequacy of sampling, was evaluated using two standards. First, precision was determined by identifying the minimum scale at which the parameter estimates varied 10% or less among the iterations for a given scale (i.e., coefficient of variation $\leq 10\%$). Second, accuracy was determined by identifying the minimum scale at which the parameter estimates at both the 5th and 95th percentiles of the iteration distribution for a given scale were within 10% of the 2.0-ha value (i.e., comparable to an effect size of 10% at a two-sided alpha of 0.05).

To evaluate the trade-off between using a single large plot and a larger number of smaller plots, we used estimates of variance from the simulated plots to calculate the necessary sample size if multiple “subplots” were sampled at different spatial scales to obtain satisfactory estimates

Table 1 Parameters of structural condition for both stands based on the full (2 ha) extent (i.e., “true”)

Stand	RS1	SV3
Mean DBH (cm)	21.9	20.4
STD of DBH	15.6	13.2
Maximum DBH (cm)	80	72.4
Basal Area (m^2/ha)	32.8	29.7
Density (trees/ha)	577	643
Large 50 (trees/ha)	31	14
R	1.00	1.02
DC	0.367	0.336
T	0.48	0.47
$DBHdiff3$	16.5	14.4
$Dd3$	0.48	0.46
SCI	6.74	6.04

DBH diameter at breast height, STD standard deviation, $Large\ 50$ density of trees over 50 cm DBH, R Clark Evans index of Aggregation, DC dissimilarity coefficient, T diameter differentiation index, $DBHdiff3$ average size difference within TINs, $Dd3$ $DBHdiff3$ scaled 0 to 1, SCI structural complexity index

for each parameter. Using the average variance across both macroplots (s^2), an effect size (E) of 10% of the average 2-ha value, and a desired alpha of 0.05, the sample size needed to estimate the mean was calculated as,

$$\# \text{ subplots} = \frac{(4 \times s^2)}{E^2}, \quad (2)$$

(Freese 1967).

Although frequently reported as a measure of horizontal structural complexity, the index of aggregation (R) presents a unique statistical and interpretive challenge. While the index provides output in the form of a continuous dataset, the interpretation is nearer to that of a class variable: values near 0 indicate aggregation/clustering, near 1 a random spatial distribution, and those significantly > 1 a regular/dispersed arrangement. Consequently, averaging across these values can smooth a combination of aggregated and dispersed plots to give the impression of spatial randomness. Thus, rather than using the mean across the 1000 iterations to calculate sample size, we report instead the proportion of plots that would be considered aggregated/clustered or dispersed as opposed to random.

All calculations and simulations were performed in Matlab V. 8.2.0 (Mathworks Inc.).

3 Results

Due to relatively low variation within simulated plots of a given scale, precision was obtained at smaller single plot extents than accuracy (Table 2). The minimum scale at which estimates were both precise and accurate varied among parameters from 0.25 ha for some structure indices to the full 2.0 ha for the density of large trees. While a single large plot of 0.5 ha would be adequate to sample most spatially explicit structure indices, most simple metrics required at least a 1-ha plot. Despite the proximity and similarity of history for the two stands, larger plot sizes were necessary for RS1 than for SV3 to achieve precision and accuracy for several parameters.

Deviation decreased with increasing scale for all parameters (Fig. 2). Although this overall pattern of typical spatial smoothing was observed in both stands, RS1 had greater overall tree density and mean tree diameters while SV3 had notably more large trees (and somewhat higher basal area). While all metrics and indices, except the density of large trees, deviated on average $\leq 10\%$ from true by 0.75 ha, the rate of spatial smoothing varied among metrics and indices. Very few iterations of most spatially explicit structure indices deviated $\geq 10\%$ by 0.5 ha (Appendix Table 5),

Table 2 Minimum scale of a single plot (in hectare) at which (1) the coefficient of variation for a given parameter was less than 10% or (2) at which both the 5th and 95th percentiles are within 10% of the 2-ha value for a given parameter

Stand	RS1		SV3	
Standard	1	2	1	2
Mean DBH (cm)	0.75	1.25	0.25	0.75
STD of DBH	0.5	1	0.25	0.5
Basal Area (m ² /ha)	0.5	1	0.25	1
Density (trees/ha)	1	2	0.25	1.5
Large 50 (trees/ha)	1.75	1.75	1.75	2
<i>DC</i>	0.1	0.25	0.25	0.5
<i>T</i>	0.1	0.25	0.05	0.25
<i>DBHdiff3</i>	0.5	1.0	0.25	1.25
<i>Dd3</i>	0.05	0.25	0.05	0.25
<i>SCI</i>	0.25	0.75	0.05	0.5

STD standard deviation, *Large 50* density of trees over 50 cm DBH, *DC* dissimilarity coefficient, *T* diameter differentiation index, *DBHdiff3* average size difference within TINs, *Dd3* DBHdiff3 scaled 0 to 1, *SCI* structural complexity index

such that their means reached $\leq 5\%$ by that same spatial scale (Fig. 2). In contrast, a comparably low number of iterations deviating $\leq 10\%$ was not observed for most simple metrics until 1 ha in size (Appendix Table 5), with means stabilizing at $\leq 5\%$ deviation at 0.75 ha for basal area and the standard deviation of tree diameters, 1.25 ha for mean tree diameter, and 1.5 ha for tree density (Fig. 2).

Consequently, the minimum sampling extent required for adequate precision and accuracy also varied by metric and index (Table 3). Although a single 0.25-ha plot would be sufficient to estimate *Dd3* and *T*, the remaining spatially explicit structure indices and simple metrics required larger extents to achieved desired levels of precision and accuracy: one 0.50 ha plot for *DC*; one 0.75 ha plot for the standard deviation of tree diameters, basal area, and the *SCI*; 1.0 ha for *DBHdiff3*; 1.25 ha for mean tree diameter; and 1.5 ha for the density of all trees. The density of large trees could not be robustly estimated in less than the full 2.0 ha plot. Conversely, if multiple smaller sampling extents were an option, then fifteen 0.25-ha subplots would suffice for all metrics and indices except the density of large trees.

Spatial arrangement varied slightly with scale (Table 4). The proportion of plot iterations with a non-random spatial arrangement declined from 15% at 0.05 ha to 0.05% by 1 ha, with both stands exhibiting a random tree arrangement at 2 ha. However, these non-random arrangements were predominantly aggregated/clustered at the smaller scales in both stands, although by 0.75 ha they were predominantly

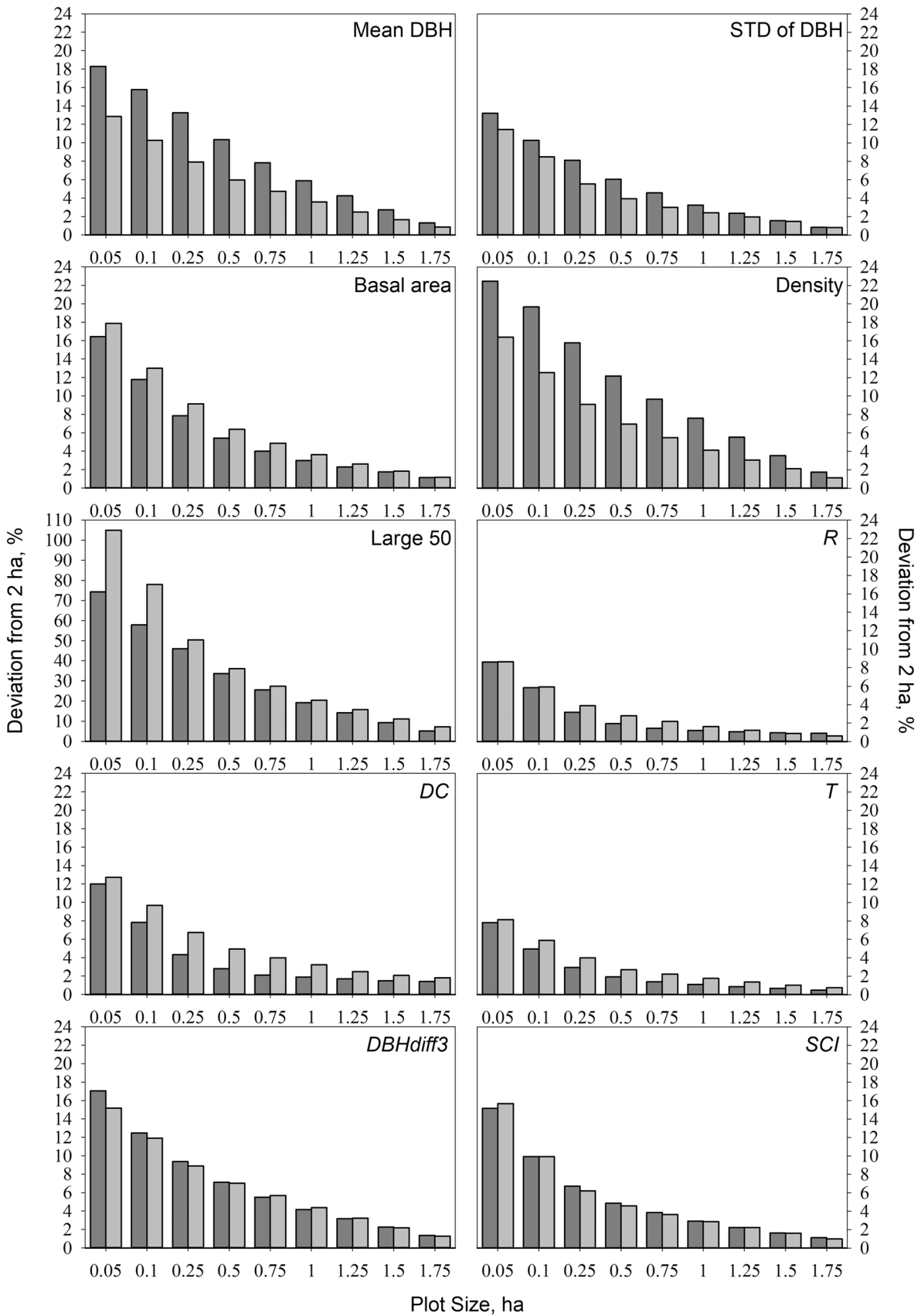


Fig. 2 Structure area curves for the two macroplots (RS1 dark grey, SV3 light grey): change with increasing scale in the mean percent deviation from the 2-ha value for the mean (mean DBH) and the standard deviation (STD of DBH) of tree diameter, basal area, the density of all trees, the density of trees over 50 cm DBH (Large 50), the Clark Evans index of Aggregation (R), the dissimilarity coefficient (DC), the diameter differentiation Index (T), the average size difference among trees within TINs ($DBHdiff3$), and the structural complexity index (SCI), based on resampling each macroplot 1000 times at different spatial scales. Note the substantially greater range of deviation for the Large 50 metric

dispersed in the SV3 stand (at which scale all iterations were already random in the RS1 stand).

4 Discussion

Sampling design is invariably faced with a dilemma: the required sampling effort depends upon the variability and spatial distribution of structural attributes within a stand, which are rarely known before an inventory is conducted. Previous research can provide some guidance, given observations that simple metrics such as mean tree diameter and density can require single plot extents on the order of 0.35 ha in beech (Král et al. 2010) and 0.50 in red pine (Zenner and Peck 2009) and old-growth *Tsuga*-mixed hardwoods (Busing and White 1993). Stands of similar management history and forest type provide the best analogues, hinting that, as in Northern hardwoods (Guillemette et al. 2012), a single plot of 0.5 ha in extent may be required to estimate basal area or of 1.0 ha to assess growth parameters. Likewise, metrics such as basal area may be most efficiently captured in

Table 4 Percent (%) of iterations (out of 1000) in which the Clark Evans index of aggregation (R) indicated aggregation/clustering (a) or dispersion (d) (as opposed to a random spatial arrangement) at each spatial scale, by stand

Scale (ha)	RS1		SV3	
	a	d	a	d
0.05	11.6	0.7	15.2	0.3
0.10	8.1	0.5	13.3	0.4
0.25	3.9	0.7	9.0	1.2
0.50	1.3	0	4.0	3.6
0.75	0.1	0	2.0	5.0
1.00	0	0	0	2.5
1.25	0.1	0	0	1.3
1.50	0	0	0	9
1.75	0	0	0	0.3
2.00	Random		Random	

mixed hardwoods using numerous small (often < 0.1 ha) dispersed subplots (e.g., Becker and Nichols 2011).

In fact, adequate estimation of simple timber metrics in the mature Eastern hardwoods forest considered here would indeed require a large single sample plot (upwards of 1.0 ha) or numerous smaller fixed area subplots (> 10 0.1 ha). Deviation of the traditional inventory metrics was still high at even large plot sizes, stabilized only at the largest extents, and most metrics could not be adequately estimated from a single plot covering less than at least 50% of the macroplot area. These results confirm the need for a high sampling intensity in even-aged stratified mixed stands, which are typically characterized by a reverse-J diameter distribution (Ashton and Kelty 2018) due to the high

Table 3 Minimum sample sizes (i.e., # of subplots) required (RS1/SV3) to obtain a robust estimate for each parameter at a given spatial scale (ha)

Scale (ha)	0.05	0.1	0.25	0.5	0.75	1	1.25	1.5	1.75
Percent of full extent	2.5%	5.0%	12.5%	25.0%	37.5%	50.0%	62.5%	75.0%	87.5%
Mean DBH	17/9	12/6	9/3	6/2	4/1	2/1	1/1	1/1	1/1
STD of DBH	11/9	6/5	4/2	2/1	1/1	1/1	1/1	1/1	1/1
Basal area	19/22	9/11	4/5	2/3	1/1	1/1	1/1	1/1	1/1
Density	33/19	25/11	15/5	9/3	5/2	3/1	2/1	1/1	1/1
Large 50	320/702	194/378	111/156	63/79	36/43	20/24	11/14	5/7	2/3
DC	9/10	4/6	1/3	1/1	1/1	1/1	1/1	1/1	1/1
T	4/3	2/2	1/1	1/1	1/1	1/1	1/1	1/1	1/1
$DBHdiff3$	20/14	10/8	5/5	3/3	2/2	1/1	1/1	1/1	1/1
$Dd3$	4/4	2/2	1/1	1/1	1/1	1/1	1/1	1/1	1/1
SCI	13/13	5/5	3/2	1/1	1/1	1/1	1/1	1/1	1/1

STD standard deviation, $Large\ 50$ density of trees over 50 cm DBH, DC dissimilarity coefficient, T diameter differentiation Index, $DBHdiff3$ average size difference within TINs, $Dd3$ $DBHdiff3$ scaled 0 to 1, SCI structural complexity index

density of small-diameter trees, and are consistent with the large sampling extents needed to reliably capture diameter distributions (Rubin et al. 2006) and improve the precision of tree density estimates in similarly structured selection forests (Jazbec et al. 2011).

However, structural features subject to strong species area curve-like trends, such as tree species composition (Busing and White 1993) or the density of large trees (Lombardi et al. 2015), often require even greater sampling effort. As is often the case (Gray 2003; Zenner and Peck 2009), large diameter trees were relatively scarce in these stands, yet are an important parameter for the restoration of Eastern forests (McGee et al. 1999; Crow et al. 2002) because they are thought to have once contributed considerably more biomass in old-growth forests than currently in young managed forests (Brown et al. 1997). Due to the high variability in capturing large trees in individual sample plots, more than ten times as many 0.1-ha subplots would be required to adequately estimate the density of large diameter trees than would have even fit within the macroplots being assessed. Alternatively, adequately estimating this parameter with a single large plot would have required the full extent of the area to be sampled (as was also seen in red pine, Zenner and Peck 2009). In the current study, even supplementary sampling through a nested plot design (e.g., a larger plot around each subplot just for large diameter trees, such as the FIA macroplot; Gormanson et al. 2018) would not have achieved sufficient accuracy and precision if it were less than the full macroplot area. Rather than untenably increasing the number of subplots or plot extent, however, such rare large trees may instead require a separate/additional sampling protocol (Thompson and Burnham 2004). Features that are known to be relatively rare within a stand may be best estimated using an entirely different sampling frame, such as the combination of fixed and variable radius plots that improves sampling precision for tree density (Packard and Radtke 2007), or point (Ritter and Saborowski 2014) or line transects (Bate et al. 1999) that can be most efficiently sampled while traveling between plots (Johnson et al. 2008; B auerle et al. 2009).

In contrast to the simple metrics, most of the spatially explicit structural indices could be adequately estimated in a single plot of less than one hectare in extent or in fewer than ten 0.1-ha subplots. Spatial arrangement (R) stabilized by 0.5 ha and spatially explicit vertical structure was adequately captured in single plots of 0.25 ha (T) or 0.5 ha (DC) in size, in keeping with previous observations in old silver birch (Maleki and Kiviste 2015) and mature red pine (Zenner and Peck 2009). However, although not as extensive as that required in savanna woodland, montane conifers or

northern hardwoods (up to 1 ha, Fonton et al. 2011; Guillemette et al. 2012; Carrer et al. 2018), a single plot of 0.75 ha would be required to capture both horizontal and vertical structure (SCI) in these mature Eastern hardwoods stands. The predominance of a random spatial distribution of trees (almost 90% at 0.1 ha) in these stands contributed to the more rapid stabilization of the structure area curves for most spatially explicit measures of structural complexity than for the simple metrics. Rapid spatial smoothing has also been observed for size class abundances and thus diameter distribution forms, which stabilized by ~ 0.15 ha in old-growth Douglas-fir (Zenner and Peck 2018) and beech (Zenner et al. 2018). Likewise, the pattern of dominance by all-sized tree neighborhoods became clear by 0.1 ha in old-growth beech (Zenner et al. 2019; 2020) and that of subsequently assigned development phases by 0.125 ha (Zenner et al. 2020). In fact, neighborhood-level tree size differences may be most clearly expressed at the fine scales (e.g., < 0.1 ha; Zenner et al. 2019) capturing individual tree processes, which coalesce at larger scales into patterns of tree size distribution (Zenner et al. 2015) (a transition in perspective across scale that is only observable using structure area curves, Zenner 2005).

As a consequence of the fine-scale structural complexity in these mature Eastern hardwoods stands, spatially explicit structural complexity indices did not necessarily require an increase in either sampling extent (for single plots) or intensity (for subplots) over what would already be required to achieve adequate estimates of the simple metrics: i.e., by the time a sufficient number of subplots was sampled for traditional timber metrics, the minimum number required for spatially explicit indices would already be met. On the one hand, this indicates that structural complexity could be tacked on to sampling protocols intended for estimating simple metrics, such as basal area, without requiring additional subplots or even a change in sampling frame from many small subplots to one large plot. On the other hand, however, greater sampling effort is nonetheless required, due to both the necessity of stem-mapping and of sampling smaller trees than is often typical (e.g., smaller than the 12.7 cm cutoff for FIA subplots, Gormanson et al. 2018). Given that the intensive sampling of neighboring trees is more suited to fixed area plots (Berrill and O'Hara 2012) and the greater efficiency of sampling one large plot over many smaller subplots (Jazbec et al. 2011), inventories assessing structural complexity in Eastern hardwoods may be optimally achieved using a single large plot (e.g., 1 ha; Grotti et al. 2019)—although an additional transect or other supplemental approach may be needed for the density of large trees when present.

The implication of these results for large national inventories relying on a small number of sparsely distributed, relatively small subplots (e.g., FIA with four spatially linked 0.07 ha plots) is that they are best suited to what they were designed for: broad trends in the “extent, condition, volume, growth, and use of trees” (Gormanson et al. 2018). Regardless of whether simple metrics or spatially explicit structural indices are involved, the high size variability in the Eastern hardwoods forest type necessitates a high degree of sampling effort when precision and accuracy are desired. Further, meaningful efforts to estimate structural complexity from data collected using inventory protocols like FIA would be futile in Eastern hardwoods, not only because complete stem-mapped data are generally lacking, but because sampling intensities are simply inadequate. This may explain why the recommended applications of FIA data only include assessments of forest structure when additional (e.g., remote sensing) data are available (Tinkham et al. 2018). Thus, the cost-effective estimation of spatially dependent forest structures in Eastern hardwoods is likely still some years away, as currently inadequate remote sensing technologies (Kekunda et al. 2019) continue to evolve (e.g., Meng et al. 2016; Kandare 2017).

5 Conclusion

It is often assumed that assessment of spatially explicit measures of structural complexity requires larger plot extents than traditional timber metrics. The results of the current study indicate that adequate estimation of simple timber metrics in spatially random mature Eastern hardwoods would actually require an even

larger single plot extent than the spatially explicit indices—particularly to estimate the density of large diameter trees. Although it could be concluded that a trade-off is inevitable and sampling designs must focus on optimizing some metrics over others, a more flexible approach may allow efficient characterization of all parameters of interest through the employment of a mixed inventory sampling scheme. Some combination approaches are already employed, such as a mixture of fixed and variable-radius plots (Packard and Radtke 2007; Gormanson et al. 2018). The current study demonstrates that basal area could be adequately estimated from ~ 10 0.1-ha subplots and that the spatially explicit indices could also be estimated if half of them were also stem-mapped. If the same level of accuracy and precision was desired for the estimation of the density of large trees, they might be most efficiently estimated through line transects connecting these subplots. Alternatively, capturing an array of forest metrics may be most cost-effectively achieved through a combination of sampling a single plot spanning 50% of the stand with an additional cruise of the remaining area for large-diameter trees. Finally, the high variability observed in these even-aged stratified mixed stands indicates that structural complexity may not be well estimated from the few subplots of small extent typically employed by national inventory programs designed to capture broad trends in forest extent and condition.

Appendix

Table 5 Percent (%) of iterations (out of 1000) with $\geq 10\%$ deviance from the 2-ha value for each metric or index, by stand (RS1/SV3)

Scale (ha)	0.05	0.1	0.25	0.5	0.75	1	1.25	1.5	1.75
Mean DBH	74/58	72/45	61/31	50/16	35/2	17/0	3/0	0/0	0/0
STD of DBH	54/47	43/31	36/15	16/7	4/< 0.1	0/0	0/0	0/0	0/0
Basal area	59/64	50/53	31/38	16/23	3/10	0/3	0/0	0/0	0/0
Density	100/100	87/100	89/100	85/89	78/84	76/70	68/62	42/42	12/36
Large 50									
<i>DC</i>	48/54	31/42	6/24	0.1/6	0/< 0.1	0/0	0/0	0/0	0/0
<i>T</i>	31/30	12/17	0.1/5	0/0	0/0	0/0	0/0	0/0	0/0
<i>DBHdiff3</i>	63/60	53/53	42/39	21/26	10/14	3/3	0/0	0/0	0/0
<i>Dd3</i>	31/36	13/18	0/5	0/0	0/0	0/0	0/0	0/0	0/0
<i>SCI</i>	60/54	42/42	21/24	7/6	< 0.1/< 0.1	0/0	0/0	0/0	0/0

STD standard deviation, *Large 50* density of trees over 50 cm DBH, *DC* dissimilarity coefficient, *T* diameter differentiation Index, *DBHdiff3* average size difference within TINs, *Dd3* DBHdiff3 scaled 0 to 1, *SCI* structural complexity index

Acknowledgements Assistance in the field and with data entry was provided by Dan Heggenstaller, Darren Wolfgang, and Jeff Watson, and Joe Harding provided site information.

Funding Funding was provided by the Department of Ecosystem Science and Management, the College of Agricultural Sciences (CAS), a CAS Seed Grant from The Pennsylvania State University, and USDA National Institute of Food and Agriculture Hatch Appropriations [#PEN04639, Accession #1015105].

Data availability The raw data are available through the Penn State Data Commons at <https://doi.org/10.26208/wx8r-fb53>.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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