

RESEARCH ARTICLE

Scale dependency of lidar-derived forest structural diversity

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Abstract

1. Lidar-derived forest structural diversity (FSD) metrics—including measures of forest canopy height, vegetation arrangement, canopy cover (CC), structural complexity and leaf area and density—are increasingly used to describe forest structural characteristics and can be used to infer many ecosystem functions. Despite broad adoption, the importance of spatial resolution (grain and extent) over which these structural metrics are calculated remains largely unconsidered. Often researchers will quantify FSD at the spatial grain size of the process of interest without considering the scale dependency or statistical behaviour of the FSD metric employed.
2. We investigated the appropriate scale of inference for eight lidar-derived spatial metrics—CC, canopy relief ratio, foliar height diversity, leaf area index, mean and median canopy height, mean outer canopy height, and rugosity (R_T)—representing five FSD categories—canopy arrangement, CC, canopy height, leaf area and density, and canopy complexity. Optimal scale was determined using the representative elementary area (REA) concept whereby the REA is the smallest grain size representative of the extent. Structural metrics were calculated at increasing canopy spatial grain (from 5 to 1000 m) from aerial lidar data collected at nine different forested ecosystems including sub-boreal, broadleaf temperate, needleleaf temperate, dry tropical, woodland and savanna systems, all sites are part of the National Ecological Observatory Network within the

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conterminous United States. To identify the REA of each FSD metric, we used changepoint analysis via segmented or piecewise regression which identifies significant changepoints for both the magnitude and variance of each metric.

3. We find that using a spatial grain size between 25 and 75 m sufficiently captures the REA of CC, canopy arrangement, canopy leaf area and canopy complexity metrics across multiple forest types and a grain size of 30–150 m captures the REA of canopy height metrics. However, differences were evident among forest types with higher REA necessary to characterize CC in evergreen needleleaf forests, and canopy height in deciduous broadleaved forests.
4. These findings indicate the appropriate range of spatial grain sizes from which inferences can be drawn from this set of FSD metrics, informing the use of lidar-derived structural metrics for research and management applications.

KEYWORDS

ecosystem structure, forest structure, forestry, lidar, remote sensing, representative elementary area, scaling

1 | INTRODUCTION

Relating observations from one scale to phenomena at another scale is a long-standing focus of ecological research (See Box 1; Wiens, 1989). Ecosystem patterns and processes vary simultaneously at fine grains and across large extents (O'Sullivan & Perry, 2013; Turner, 1989); however, measurement of the finest details lacks the spatial extent required to understand large scale processes. Conversely, measurement at large spatial extents omits or aggregates fine-grain features. Ecological processes occur at

scales from molecular to global, but their apparent importance varies with scale of observation as spatial patterns that are highly variable at one scale may appear uniform at another (Levin, 1992). The challenge to understanding the scale dependency in the relationship between ecological pattern and process (Watt, 1947) lies in bridging 'smaller-area-higher-detail' and 'larger-area-lower-detail' data (Calders et al., 2020). While there is no inherent natural scale at which ecosystems should be analysed (Levin, 1992), examining the interactions between ecological patterns and processes requires measurements aligned with the scale of the process of interest. Determining the 'right' scale to study a process remains an ongoing challenge, with workers often defaulting to the native scale of the data or the specific goals of a study (Elith & Leathwick, 2009).

Here we focus on the question of scale and scale dependency in measuring forest structure and structural dynamics—the study of which has rapidly progressed in the preceding decades due to advances in remote sensing technology and theory (van Leeuwen & Nieuwenhuis, 2010). Remote sensing provides the ability to quantify key forest structural parameters of primary research, management, policy and conservation interest through the use. Remote sensing-derived metrics of forest structural diversity (FSD) describe the heterogeneity, arrangement and configuration of vegetation elements within forests and forest canopies (Hakkenberg & Goetz, 2021). FSD drives ecological processes at local to global scales (Ehbrecht et al., 2021). At the scale of the individual tree (10–100 m²), light interception, absorption and use-efficiency are determined not only by the amount of leaf area, but also by leaf arrangement and architecture (Atkins, Fahey, et al., 2018; Cavender-Bares et al., 2004; Ellsworth & Reich, 1993; Hardiman et al., 2013; McNeil et al., 2008). Beyond the individual, at the stand scale (1000–10,000 m²), structural diversity affects understorey plant competition (Valladares et al., 2016), microclimate (Frenne et al., 2019, 2021; Zellweger et al., 2019),

BOX 1 Defining terms

The term 'scale' has many meanings across ecological and geophysical disciplines. Here, we use scale as the nested levels of organization and variation of ecosystem structural diversity. We use the term 'extent' for the spatial or geographical size of the domain of consideration, and 'grain' to indicate the resolution or degree of detail within that domain. In this sense, 'scaling' refers to the transfer of information observed at one extent, grain or level of organization to another. Here, upscaling is transferring local information to larger resolutions (i.e. extent or grain) or aggregating local measurements into regional or global parameters. Upscaling allows inference about the characteristics of higher levels of organization based on information observed from lower levels of organization. Then downscaling is to move from large to local scales, or disaggregation (Wu & Li, 2009), inferring the characteristics of lower levels of organization based on information observed from higher levels of organization.

recruitment, forest productivity (Gough et al., 2019), and, ultimately, species diversity and composition (Hakkenberg, Peet, et al., 2018; Hakkenberg, Zhu, et al., 2018). Canopy tree diameter and height determine canopy volume, as well as gas exchange for photosynthesis and transpiration, with impacts for above-ground biomass, carbon storage and productivity. These effects have consequences beyond just primary producers, also influencing habitat suitability, herbivory rates, predator-prey dynamics and insect outbreaks (Ehbrecht et al., 2021; Garabedian et al., 2017).

FSD can be estimated from many different approaches that allow recording of data at different resolutions and extents and via different sampling schema. Traditional forest structural assessments often rely on manual instruments (e.g. measuring tapes, prisms, hypsometers) that provide data at limited spatial extents, typically at the 'plot' level—25 ha or smaller area in most cases. Traditional approaches tend to be logistically difficult and costly, limiting the density, extent and frequency of assessment. Scaling these estimates of structure beyond an individual tree or plot scale ($\sim 100 \text{ m}^2$) requires statistical techniques or data fusion approaches. Remote sensing methods are a popular and powerful means of scaling estimates of FSD as well as a means of assessment at much broader scales. Terrestrial, proximal and airborne remote sensing methods can provide near leaf-level ($<1 \text{ m}^2$) resolution, while satellite observations have footprints that encompass many individual plants or stands ($\sim 1000\text{--}10,000 \text{ m}^2$). However, there are explicit sensor-specific considerations in moving from raw, off-sensor data to analysis-ready data. Models and algorithms are used to extract information from raw remote sensing data to create viable data products. Remote sensing data often have an implicit observation scale (e.g. transects of arbitrary length, aggregation of data points within areas of arbitrary dimensions, spatial grain determined by technical limitations), and this observation scale may or may not match the relevant scale of the physical processes or phenomena of interest. Often logistics, cost, technological or physical constraints prevent alignment of observation and process scales, requiring cross-scale inferences based on incomplete, unavailable or unobtainable data.

Light detection and ranging (Lidar) is a form of active remote sensing that provides multidimensional characterization of vegetation structure. Lidar sensor platforms may be terrestrial, airborne or spaceborne, each with unique advantages, limitations and optimal observation scales (Guo et al., 2021). Terrestrial lidar systems provide detailed information (mm to cm resolution) on fine detail tree structures (e.g. leaves, stems and branches) at small local extents ($<1000 \text{ m}^2$; Wilkes et al., 2016) but have limitations in capturing upper canopy structures (LaRue et al., 2020). Terrestrial lidar data can also be time-consuming to both acquire and process. Airborne lidar systems provide more granular information on canopy structures from local to landscape scales (Almeida et al., 2019), though the design of airborne lidar campaigns has significant impacts on the quality of airborne lidar (Béland et al., 2019; Shao et al., 2019). Both airborne and terrestrial lidar data are most often structured as point clouds, a data structure consisting of x, y and z

positions of a lidar return. Point clouds represent continuous coverage within the scan area, creating one key difference separating lidar data from many other remote sensing data structures (e.g. Landsat or MODIS imagery), mainly the lack of a native spatial grain. As that spatial scale of many studies is often determined by the spatial grain of the data used—30 m in the case of Landsat—no such limitation exists on the use of lidar point cloud data. The spatial resolution is determined by the user when aggregating point cloud data. There are two common approaches to address this when moving from point cloud data to FSD metrics. The first is area-based calculation whereby a user defines a grid extent and cell size and processes data to that grid cell resolution. The second is individual tree detection where crown delineation algorithms are used to locate individual trees, as polygons, in a dataset before further processing occurs. Here we focus on the area-based approach as it is the most suitable method for fusing lidar with other gridded datasets. Given these considerations, it is vital that we create robust ecological and statistical frameworks for integrating lidar data with information obtained at divergent scales in an ecologically meaning and statistically defensible manner.

These scaling concerns are particularly relevant to spaceborne lidar systems—including the Global Ecosystem Demography Investigation (GEDI) and ICESat2—that provide structural information at broad, even global scales but are not yet capable of providing continuous coverage, often leaving large spatial gaps between each lidar pulse (Dubayah et al., 2020) returning only vertical structural information integrated within the area of the lidar footprint—approximately 25 m in diameter for GEDI and 13 m for ICESat2 (Hancock, 2019; Liu et al., 2021).

A common approach to address scale in ecological studies is to do an analysis across several scales and select the scale at which the relationship between an environmental factor and phenomenon of interest (e.g. forest productivity) is strongest, considering this the 'intrinsic scale of the process' (Holland et al., 2004; Lechner et al., 2012). Selecting the desired scale based on this correlation emphasizes the studied relationship but does not consider that aggregation across scales can itself influence the outcome (J. Wu, 2004). A review of 71 multi-scale studies of species-landscape structure relationships showed that observed scales of effects were likely driven by limited ranges of scales evaluated rather than innate attributes of species (Jackson & Fahrig, 2015). Frequently, forest structure is measured at a scale arbitrarily set for convenience or based on the constraints of the measurement instrument of choice rather than informed by an understanding of the relationship between structure and scale. In addition to these theoretical considerations, there are also practical, logistical challenges. For example, consider leaf area, which is often estimated with leaf area index (LAI), an expression of leaf area per unit ground area. Leaf area is estimated at grain sizes from the individual tree or plot scale (10s of m^2) to that of the landscape (1000s of m^2). Leaf area estimated at larger grain sizes may be suitable for use cases such as global climate models but is unsuitable for surveying the foraging habitat of a small mammal with a limited spatial range. Conversely, small-grain size (e.g. 1–10 m grain size) estimates of leaf

area would be untenable for global climate models while ideal for small animal studies.

The central issue with an intrinsic scale approach is the circular nature of the underlying assumption. Basing the scale of structural assessment on its correlation with the environmental factor of interest does not consider the stationarity—where the mean and a variance no longer change—of the structural variable considered nor whether the grain size adequately represents either the magnitude or variance of the variable. Such an approach only provides information on the relatedness of these variables to each other, with no explicit consideration of the numerical space in which either exist—with the worst-case scenario being that any relationships discovered are simply statistical artefacts. The representative elementary area (REA) concept, used to describe the appropriate scale to describe the rainfall-runoff process among catchments of varying size (Beven et al., 1988; Wood et al., 1990), is one heuristic with strong theoretical foundations for addressing this issue. REA can be defined as the ‘...smallest discernible point which is representative of the continuum’ (Wood et al., 1990). Alternatively, REA can be defined as the scale at which the variability of response falls to an acceptably low level. This second definition is a more operationally defined approach (Hand, 1996) but may be more suitable for some applications. Here we have chosen to focus on the first definition of REA to define the stationarity of forest structural metrics. We approach this using changepoint analysis to identify the points of stationarity based on changes in magnitude and variance with increasing spatial scale of inference. To extend our leaf area example, using a very fine grain size of 1 m may result in incredibly high variance as such a fine grain size is capturing the intra-canopy variance of individual trees while also overrepresenting small forest gaps, thus creating an unrepresentative estimation of leaf area. If we take a stepwise approach of calculating leaf area at steps of increasing grain size, we can then examine how the variance and magnitude of those estimates change with increasing area of consideration. By fitting line segments to the intervals between grain sizes, we can compare the slope of those line segments. Changepoints can be identified using a statistical analysis (e.g. segmented regression, Bayesian changepoint analysis) that identifies when the slopes of those line segments differ significantly. The changepoint—the identified point in this relationship where the response of the independent variable (leaf area, in our example) changes abruptly in response to the dependent variable (grain size)—can then be interpreted as the point at which stationarity occurs. These points of stationarity thus represent the REA of FSD calculations within our structural data—the cell size or grain at which estimation of structure is representative of the forest. Estimations below the REA do not represent the forest, but rather individual forest components. This approach is highly reproducible and allows for robust hypothesis testing, while addressing the consideration that lidar point cloud data have non-native spatial grain, thus requiring a statistical consideration to determine the appropriate spatial grain. However, under potential use cases, a pre-defined error threshold may be an acceptable or even desired alternative to this approach.

We assess the REA of eight commonly used lidar-derived metrics describing five structural diversity categories: (1) canopy arrangement; (2) canopy cover (CC); (3) canopy height; (4) canopy structural complexity and (5) leaf area and density (Atkins, Bohrer, et al., 2018; Fahey et al., 2019). We ask (1) What is the REA necessary to characterize the magnitude and variance of these FSD metrics? (2) Does REA vary as a function of forest type?

2 | MATERIALS AND METHODS

2.1 | Site selection

We used airborne lidar data collected by the National Ecological Observatory Network (NEON) Airborne Observation Platform (AOP; Kampe et al., 2010) from nine NEON terrestrial observation sites (Table 1; Figure 1) (Kao et al., 2012): (1) Bartlett Experimental Forest, NH, USA (BART); (2) Harvard Forest, MA, USA (HARV); (3) Great Smoky Mountains National Park, TN, USA (GRSM); (4) Lower Teakettle, CA, USA (TEAK); (5) Ordway-Swisher Biological Station, FL, USA (OSBS); (6) Smithsonian Environmental Research Center, MD, USA (SERC); (7) Talladega National Forest, AL, USA (TALL); (8) University of Notre Dame Environmental Research Center, MI, USA (UNDE); and (9) Wind River Experimental Forest, WA, USA (WREF).

NEON site selection involves many logistical considerations including, but not limited to how representative the site must be of wildland conditions within a site's respective ecoclimatic domain, proximity to other sites within the domain for logistical convenience, long-term accessibility via permitting and secure land tenure, unimpeded airspace availability for regular air surveys, if possible; and comparability to other sites within the domains (See <https://www.neonscience.org/field-sites/about-field-sites> for more information).

2.2 | Data processing and analysis

For each site, we analysed between 900 and 2000 ha of lidar acquisition data including the airshed footprint of the eddy covariance tower at each site and the forest inventory plots adjacent to that eddy covariance tower. All NEON AOP data were collected during the peak growing season as determined based on long-term analysis of periods within 90% of peak greenness (Kampe et al., 2010), collected between 2016 and 2018, with a point density range of 4–32 points m⁻²—all above the range of acceptable point density for FSD metric calculation (LaRue et al., 2022). Lidar data were processed in R 4.1.2 (R Core Team, 2022) using the `lidR` package (Roussel et al., 2022). Before structural metrics were calculated, data were normalized to a height datum of 0 using the `normalize_height()` function from the `lidR` package using a triangular irregular network algorithm with bilinear sampling with

TABLE 1 Site table showing full site details including geographical position, forest type and composition, lidar data acquisition time, and site-level means (based on 25 m spatial resolution aerial lidar data) of canopy cover (CC), mean outer canopy height (MOCH) and leaf area index (LAI). Additional information on lidar technical specifics are contained in [Supplementary Materials](#). See also National Ecological Observatory Network (NEON) Field State Information for further details: <https://www.neonscience.org/field-sites/explore-field-sites>

Site	Forest type & dominant canopy species	Latitude & longitude	Lidar acquisition time frame	Forest structure at 25 m grain
Bartlett Experimental Forest, NH, USA (BART)	Mixed—American beech, Eastern hemlock, and Red maple	44.06, -71.28	August 2018	CC—82.1% MOCH—15.1 m LAI—5.1 m ² m ⁻²
Great Smoky Mountains, TN, USA (GRSM)	Deciduous broadleaf—Yellow poplar, Red maple	35.68, -83.50	September 2016	CC—90.2% MOCH—18.4 m LAI—7.7 m ² m ⁻²
Harvard Forest, MA, USA (HARV)	Mixed—Northern red oak, Eastern hemlock	42.53, -72.17	September 2018	CC—84.8% MOCH—17.8 m LAI—4.6 m ² m ⁻²
Ordway-Swisher Biological Station, FL, USA (OSBS)	Mixed—Turkey oak, Longleaf Pine	29.68, -81.99	September 2018	CC—33.5% MOCH—5.2 m LAI—0.8 m ² m ⁻²
Smithsonian Environmental Research Center, MD, USA (SERC)	Deciduous broadleaf—Yellow poplar, American beech, American sweetgum	38.89, -76.56	July–August 2017	CC—65.4% MOCH—14.5 m LAI—3.7 m ² m ⁻²
Talladega National Forest, AL, USA (TALL)	Mixed—Chestnut oak, Yellow poplar, Mixed pine	32.95, -87.39	April 2018	CC—71.8% MOCH—16.2 m LAI—3.5 m ² m ⁻²
Lower Teakettle, CA, USA (TEAK)	Evergreen needleleaf—Red and White Fir, Lodgepole pine	37.00, -119.06	June 2018	CC—49.9% MOCH—9.4 m LAI—2.0 m ² m ⁻²
Univ. of Notre Dame Environmental Research Center, MI, USA, (UNDE)	Mixed—Sugar and Red Maple, Balsam fir	46.23, -89.53	September 2017	CC—64.8% MOCH—10.3 m LAI—2.8 m ² m ⁻²
Wind River Experimental Forest, WA, USA (WREF)	Evergreen needleleaf—Douglas fir, Western hemlock	45.82, -121.95	July 2018	CC—82.7% MOCH—21.4 m LAI—6.6 m ² m ⁻²

normalization applied directly to the point cloud. A height threshold of 50 m for all sites but WREF, where 75 m was used, was set to eliminate noisy outlier data or data artefacts that occurred during lidar acquisition and pre-processing.

2.3 | FSD metrics and grain size

We calculated eight lidar-derived structural metrics from five structural diversity categories: (1) canopy arrangement, (2) CC, (3) canopy height, (4) canopy structural complexity and (5) leaf area and density (Atkins, Bohrer, et al., 2018; Fahey et al., 2019; LaRue et al., 2019) at 12 different grain sizes (5, 10, 25, 30, 50, 60, 90, 100, 150, 250, 500 and 1000 m; a range of 25–1000,000 m²) (Figure 1).

Each lidar-derived structural metric was calculated using the *grid_metrics* function in the *lidR* package (Roussel et al., 2022), except for LAI which was used to quantify leaf area and density and was calculated using the *CANOPYLAZR* package (Kamoske et al., 2019, 2021) as described below.

Canopy arrangement describes the position and relationships of canopy elements in space and includes structural metrics such

as clumping index, canopy relief ratio (CRR) and canopy porosity (Atkins, Bohrer, et al., 2018). Here we used the CRR (Parker et al., 2004; Pike & Wilson, 1971) to estimate canopy arrangement. CRR is calculated as:

$$\text{CRR} = \frac{\bar{z} - z_{\min}}{z_{\max} - z_{\min}}. \quad (1)$$

CRR is calculated where for each pixel, $\bar{z}$ is the mean lidar return height, $z_{\min}$ is the minimum return height and $z_{\max}$ is the maximum return height of that pixel.

CC metrics differ from those describing canopy arrangement as they are inherently two-dimensional and include metrics such as gap fraction and CC (Atkins, Bohrer, et al., 2018). We used the structural metric CC which is the proportion of the ground covered by forest canopy (above 2 m) in units of percent. CC is approximately the inverse of gap fraction, another commonly estimated forest structural property. CC was calculated for each pixel using lidar returns as:

$$\text{CC} = \left(1 - \frac{\sum_{i=1}^n z_{iZ>2}}{n} \right) \times 100, \quad (2)$$

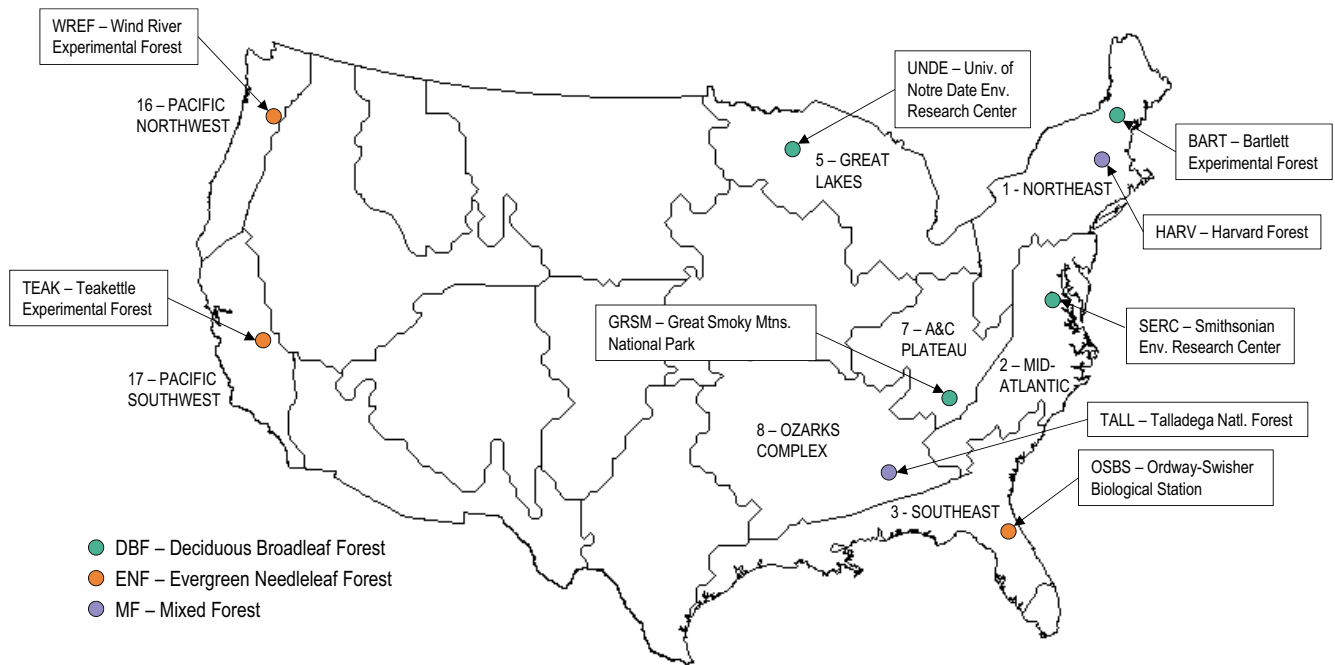


FIGURE 1 A map illustrating the location of the National Ecological Observatory Network (NEON) sites used in this study with their associated NEON Ecoclimatic Domains and their primary plant functional type association, indicated by the colour, see inset legend.

where z is the height of the lidar return and n the total number of all lidar returns in that pixel.

Canopy height metrics summarize the vertical patterns of vegetation distribution (Atkins, Bohrer, et al., 2018). To estimate canopy height, we used three separate metrics, mean canopy height (H_{Mean}), median canopy height (H_{Median}) and mean outer canopy height (MOCH; also known as local outer canopy height). H_{Mean} and H_{Median} were calculated based on the mean and median, respectively, of lidar return heights in each pixel (Atkins, Fahey, et al., 2018). MOCH was calculated as the mean of first returns only for each pixel, with the assumption that first returns do not enter the canopy and therefore are representative of the outer surface area.

Canopy complexity or heterogeneity describe the horizontal and vertical variance of canopy elements within canopy space. To estimate canopy structural complexity, we used foliar height diversity (FHD), an application of the Shannon–Weiner diversity function applied to the vertical distribution of canopy leaf area or in this case, lidar return heights (MacArthur & Horn, 1969; MacArthur & MacArthur, 1961) that describes forest layering, an important consideration for ecosystem demography modelling (Fisher et al., 2018). The `lidR` packages do not have a native calculation for FHD, but rather includes a calculation for entropy ($H(z)$) a metric rooted in information theory (Shannon, 1948) which is FHD normalized by the maximum lidar return height. To calculate FHD, we multiplied $H(z)$ by the log of the maximum return height:

$$\text{FHD} = H(z) \times \log_{\text{max}}. \quad (3)$$

Rugosity is the standard deviation of outer canopy heights, specifically first returns only (Parker et al., 2004; Parker & Russ, 2004). Rugosity

provides an assessment of heterogeneity based on the variability of the system, rather than entropy in the case of FHD; here that variability is based on the variability of outer surface heights (Valbuena et al., 2021).

To estimate leaf area and density, we used LAI as calculated using the `CANOPYLazR` package (Kamoske et al., 2019) which utilizes the MacArthur–Horn algorithm for calculating leaf area (MacArthur & Horn, 1969). Rather than calculating individual extinction coefficients for leaf area density (LAD) calculation for each site, we used a global extinction coefficient of 0.5 to approximate foliage distribution within the canopy (Richardson et al., 2009). This extinction coefficient of 0.5 was used instead of individual coefficients for each dataset given the paucity of necessary, site-specific coefficients. First, we normalized the point cloud to height above the ground as described above, and then calculated LAD by counting the number of lidar pulses that enter and exit each voxel in each vertical column with at least one corresponding ground return. We defined voxel depth as 1 m and with x and y dimensions corresponding to each tested spatial grain. Due to the wide variety of spatial grains used in this study, we removed the bottom 5 m of the canopy from calculations to limit the effects of noise caused by topographic variation in the LAD results and to have an easily comparable dataset (Kamoske et al., 2019, 2021). LAI was then calculated by taking the sum of all LAD values, above 5 m, within a column of voxels.

2.4 | Change point analysis and REA determination

Rasters of each calculated lidar metric, for each site, were mosaicked and then sampled using a uniformly spaced sampling grid of

16 sampling points per 1×1 km tile for grains of less than 250 m, 4 sampling points per 1×1 km tile for 500 m grain size and 1 sampling point per 1×1 km tile for the 1000 m grain via the *sampleRegular* function from the *RASTER* package (Hijmans et al., 2020). Data were then filtered to pixels with a minimum of 5 m canopy height (based on the 99th percentile return height) and 25% CC, motivated by the definition of what constitutes a 'forest' in Hansen et al. (2010) and the lidar structural analysis method outlined in (Atkins et al., 2022). In all, 100 randomly sampled points for each spatial grain between 5 and 250 m were retrained for further analysis, as were all data at the 500 and 1000 m grain ($n = 36$ and 9, respectively). The mean, standard deviation and coefficient of variation (as a measure of variance) for each metric was calculated for each site at each spatial grain from filtered, sorted data. The REA for each site was determined based on changepoint analysis with piecewise or segmented regression using the *SEGMENTED* package in R (Muggeo, 2022). First, we identified changepoints using the *selgmented* function with the 'AIC' algorithm which applies Akaike information criteria (Akaike, 1974) to inform changepoint identification by selecting changepoints by minimizing information loss and optimizing the trade-off between bias and variance within the data, similar to the approach of using AIC in model selection. We then tested the statistical significance of any identified changepoints for both the magnitude (mean) and the coefficient of variation (CV) of each response variable using a Davies Test via the *davies.test* function (also in the *SEGMENTED* package) which tests for a non-zero difference-in-slope parameter of a segmented relationship with a null hypothesis that no change in

slope exists. Each statistically significant changepoint for each site is reported with uncertainty quantified as 95% confidence intervals. The REA necessary to quantify each structural diversity metric is reported as the median value of the first statistically significant changepoints across all sites with identified changepoints for that metric with variability reported as the interquartile range (IQR) to account for uncertainty.

2.5 | Testing for differences among forest types

We considered forest type using the plant functional type (PFT) approach from Bonan et al. (2002) classifying forests as either mixed forest (MF, containing between 30% and 70% of both broad and needleleaf species), deciduous broadleaf (DBF, with greater than 70% composition of broadleaf species) or evergreen needleleaf forests (ENF, with greater than 70% composition of needleleaf species). To be conservative, we show differences among PFTs using the IQR, inferring differences when those ranges do not overlap.

3 | RESULTS

The nine forested ecosystems selected for this analysis range in forest height from a mean of 5.2 m at OSBS to 21.4 m at WREF, in CC from a mean of 33.5% at OSBS to 90.2% at GRSM and in leaf area from a mean $0.8 \text{ m}^2 \text{ m}^{-2}$ at OSBS to $7.7 \text{ m}^2 \text{ m}^{-2}$ at GRSM as estimated

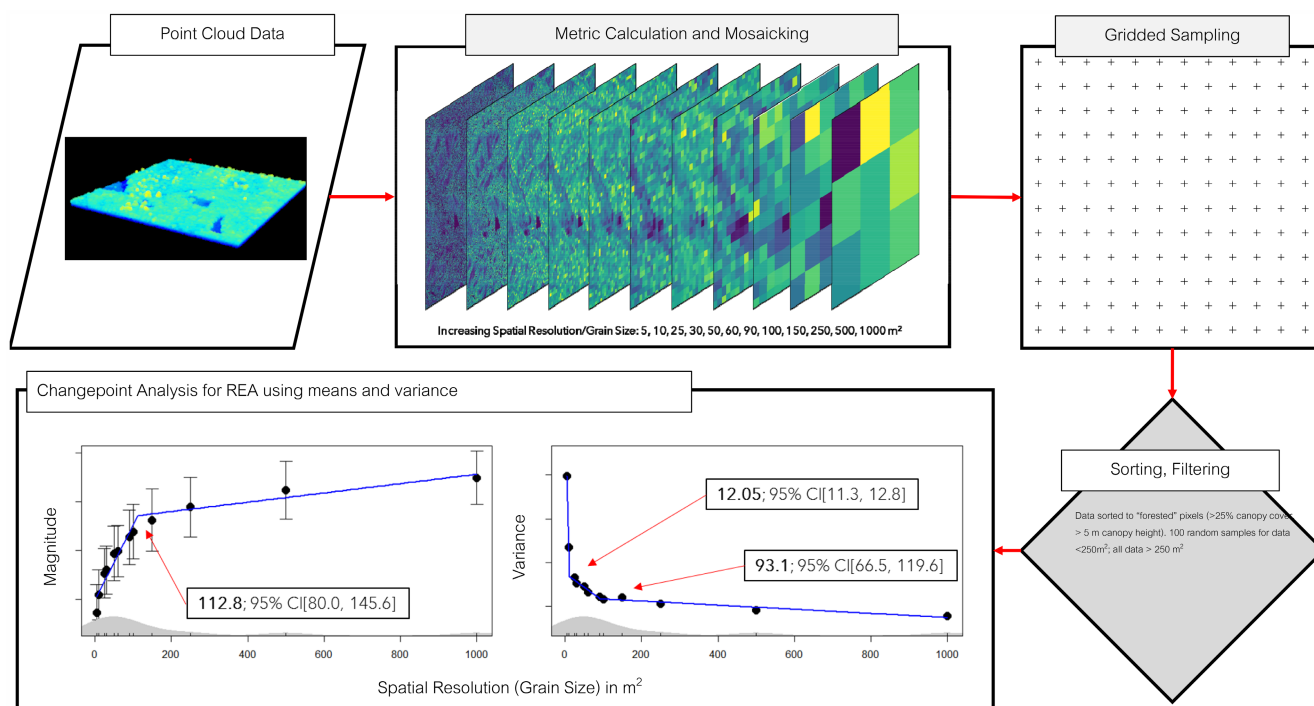


FIGURE 2 Workflow diagram showing how we move from our 'raw' lidar point cloud data, through our stepwise calculation of lidar structural metrics at increasing spatial grain, then to our gridded sampling, then to sorting and filtering the data to only include forested pixels (pixels with >25% CC and heights >5 m, randomized sampling of a standard number of points, then to the changepoint analysis with sample output.

at 30 m grain (Table 1; Figure 2). These sites are broadly representative of the forest complexity observed at the continental scale for the United States (Atkins, Fahey, et al., 2018) and of similar systems globally (Potapov et al., 2021).

REA analysis showed that there were differences among FSD categories, but these differences were constrained within structural categories. CC, canopy arrangement and canopy complexity exhibit REA values around 30 m grain and stable range of ~15–75 m grain based on the IQRs of first changepoints identified among CC, CRR, FHD and rugosity (R_T) (Figure 2). REA for measures of canopy height (H_{Mean} , H_{Median} and MOCH) skewed higher, in the 40–100 m range with higher dispersion as well with an IQR of ~30–200 m. Leaf area, as estimated using LAI, was around 50 m also with high dispersion with an IQR of ~10–130 m (see Supporting Information for further details).

3.1 | Patterns within structural categories

Variability in REA, as assessed using the changepoints of the coefficient of variation for each structural metric, also exhibited broad dispersion. The highest REA observed was for CC_{CV} at ~90 m with

an IQR of ~35–265 m with the lowest observed being LAI_{CV} at ~12 m and a highly constrained IQR of 12–13 m (Figure 3).

Our assessment of CC showed that the REA of CC was 30.0 m², based on the median of 8 out of a possible 9 statistically significant identified first changepoints from our data across all sites. NEON site TALL was the only site with no identifiable changepoint for CC. Second changepoints were identified for BART (213.4 m) and SERC (198.9 m) only. The REA for CC variability, based on the coefficient of variation of CC, was less obvious. Two sites, TALL and TEAK, had two identified changepoints at 25.0 and 36.2 m, respectively, and the second at 450.9 and 481.8 m, respectively. Only one changepoint was identified for both OSBS (446.4 m) and SERC (139.9 m). Other sites had no significant changepoints.

CRR was highly consistent across sites with an REA of 33.3 m and an IQR of 30.0–35.8 m based on first changepoints identified at all sites. Second changepoints were found for 7 of 9 sites, with the median of those values at 206.2 m and an IQR of 202.5–209.8 m.

FHD REA was stable at 26.1 m and an IQR of 13.5–32.4 m based on 8 out of 9 sites with significant change points. Second changepoints were identified for five additional sites with a median of 161.3 m but much higher IQR, 77.0–211.4 m. FHD_{CV} was consistent with FHD_{Median} at 33.0 m and an IQR of 25.5–38.5 m.

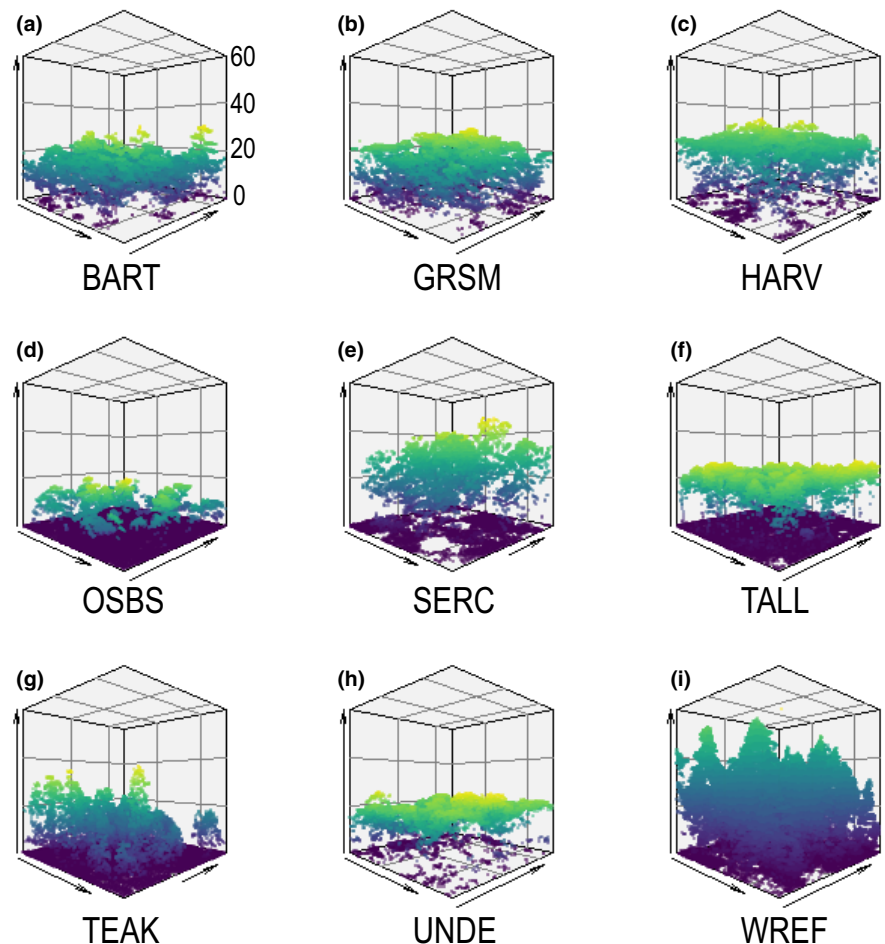


FIGURE 3 Lidar point clouds of 50×50 m resolution taken from each site showing differences in forest structure for visual comparison. Lower stature, lower complexity forests such as OSBS (d) differ starkly from taller stature, more complex forests such as GRSM (b) and WREF (i). Sites (a–i) are labelled using NEON abbreviated site codes (e.g., BART, GRSM), see Table 1 for full site descriptions.

Rugosity or top rugosity (R_T) was highly constrained across all sites with a median value of 29.8 m² and an IQR of 27.4–35.0 m with the $R_{T,CV}$ showing similar statistical behaviour with a median of 26.5 m and a constrained IQR of 25.2–29.1 m.

The highest observed overall change points were among measures of canopy height. However, more sites had no observed change points for canopy height metrics—either for the magnitude or variability—than other structural metrics. Canopy height metrics also had the largest IQRs.

3.2 | Differences among forest types

We found differences in REA among forest types for FSD measures of CC, forest height and leaf area (Figure 4). ENF sites have a higher CC REA (~30–115 m) than DBF sites (~20–30 m; Figure 4), whereas MF sites fall within the range of ENF sites (~100 m), DBF or MF (Atkins et al., 2022). The starkest difference observed is that REA for CC is much higher in needleleaf forests (ENF) than either mixed (MF) or broadleaf forests (DBF), but the REA for variability

in CC is much lower in needleleaf forests (ENF). The REA of canopy height measures tended higher in DBF sites (~200 m) as compared to MF or ENF sites; however, this is partially a function of the lack of identified change points for many DBF sites which warrants further inspection. We also find that the REA of LAI is more variable for ENF sites and that complexity/heterogeneity measures largely agree among PFTs (Figures 5 and 6).

4 | DISCUSSION

Quantifying scale dependence in lidar remote sensing of FSD reflects the need to determine optimal scales that match considerations of technical constraints among lidar sensors with the characteristic scales of forest elements observed. While the technologies are new, the strategy is not. For example, in their study on landscape patch dynamics, Busing and White (1993) found an inverse relationship between variance in structural metrics (e.g. basal area and biomass) and grain size that was approximately linear in log–log space. Our findings indicate spatial grain sizes of between 25 and 75 m

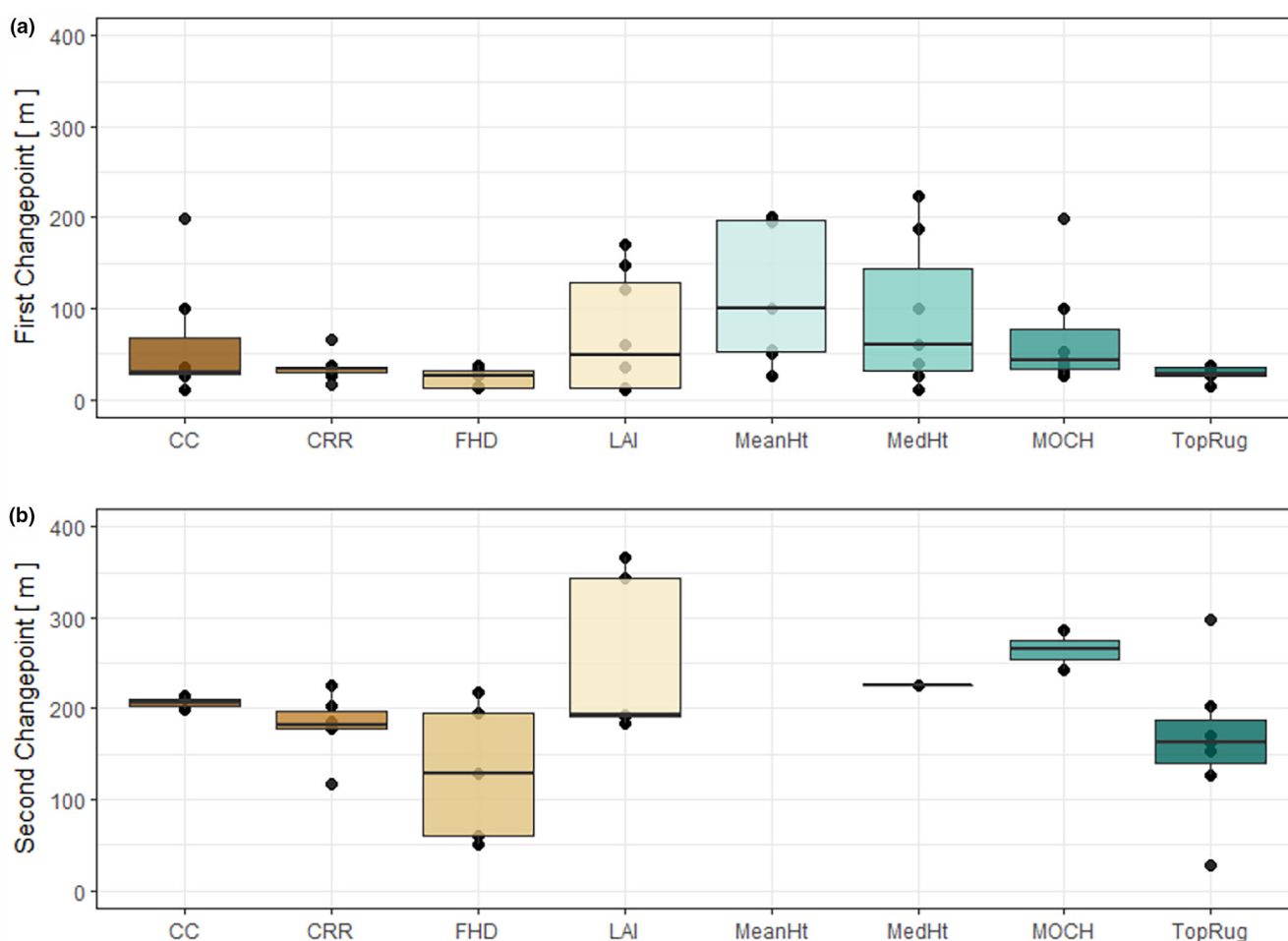


FIGURE 4 (a) Box plot of the first statistically significant change point (grain size in meters) of the magnitude of structural diversity metrics identified using change point analysis for nine forested ecosystem sites in North America. The black line in the middle of the box is the median estimate with the lower and upper lines showing the 25th and 75th percentiles, respectively. (b) Box plot of second statistically significant change points. Absence of any box means no change points were found.

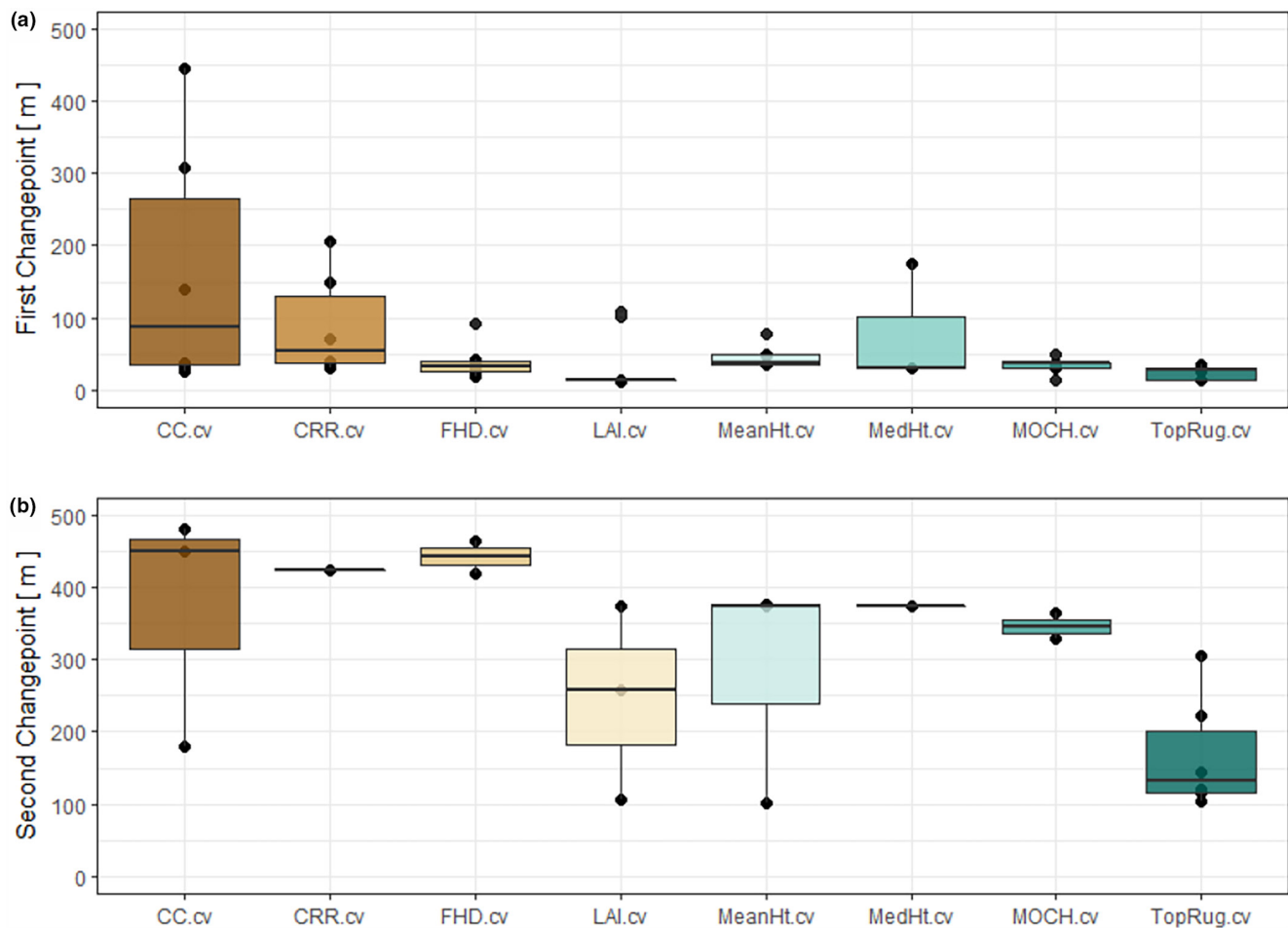


FIGURE 5 (a) Box plot of first statistically significant change points (grain size in meters) of the coefficient of variation (CV) of each structural metric identified using change point analysis for nine forested ecosystem sites in North America. The black line in the middle of the box is the median estimate with the lower and upper lines showing the 25th and 75th percentiles, respectively. (b) Box plot of second statistically significant change points. Absence of any box means not change points were found.

sufficiently capture the REA of the magnitude of lidar-derived FSD metrics within the structural categories of CC, canopy arrangement, canopy leaf area and canopy complexity across multiple forest types. For small-statured herbaceous plants in nutrient-rich temperate mixed forests, studies have found scale-dependent effects of forest structure (e.g. CC) on plants species richness to peak at intermediate scales (400–1000 m²), though this scale is dependent, critically, on a third interacting factor: soil fertility (Hakkenberg et al., 2020). For example, in the poor soils of fire-maintained longleaf pine ecosystems where frequent burns create large gaps, but also supply a burst of readily available nutrients for small-statured plants, structure's scale-dependent effect on diversity peak at far smaller scales (10–100 m²; Palmquist et al., 2015). Lidar-derived FSD predictors of structure largely align with these results, with gappy, xeric ridgetop understorey plant diversity best predicted at scales <400 m², while plant diversity in the tall, closed canopies of mesic old-growth forests were found to peak at scales above 1000 m² owing in part to issues of geolocational imprecision between remotely sensed and field data, as well as characteristic scales of crown and gap size dynamics of these large-statured forests (Hakkenberg, Peet, et al., 2018;

Hakkenberg, Zhu, et al., 2018). However, to accurately capture the REA of structural attributes such as canopy height, larger grain sizes between 35 and 150 m may be necessary. This can be approached at more granular level if we consider forest type (Figure 4). While complexity and heterogeneity measures such as CRR, rugosity and FHD behave uniformly regardless of forest type, measures of CC and forest height diverge—with needleleaved forests (ENF) requiring a higher REA to capture CC, while broadleaved forests require higher REA to capture forest height measures.

In some instances, we found secondary change points at larger spatial grain sizes for some metrics—indicative of potential differences in the spatial dynamics between the stand level and the landscape (Hardiman et al., 2018). A rigorous test of this hypothesis is not possible with the NEON AOP dataset or with similar aerial lidar collections given the spatial extent of aerial lidar collections. Wall-to-wall coverage on the order of 100–1000s of km² would be necessary. Data fusion approaches combining spaceborne lidar with other remote sensing data (e.g. synthetic aperture radar) offer a potential means to explore landscape or even global variation (Potapov et al., 2021; Qi & Dubayah, 2016).

The necessary REA to capture structural variability—here assessed using the coefficient of variation of each structural metrics—is more inconsistent and less universal as CC and canopy arrangement metrics require between 35 and 125 m spatial grain size and canopy complexity requires ~25–30 m. Leaf area is a special case where the estimated REA for variability is within plus or minus 0.5 m of 12 m spatial grain. Consideration of statistical variance in forest structure is an underexamined area. Work in limnology and aquatic ecology has shown that variance can be a leading indicator of functional instability and future regime shifts (Carpenter et al., 2011; Palmer et al., 1997; Seekell et al., 2011), yet transfer of these ideas to terrestrial work could be more fully realized. We show that, generally, the REA necessary to capture structural variability is less than necessary to capture the magnitude of any structural measure, indicating that if we primarily consider the REA necessary to capture the magnitude of FSD, we are also adequately incorporating the variance and variability as well, a major consideration for scaling applications.

Previous work has shown that the sampling density of NEON lidar acquisition, specifically lidar pulse and point density, is robust for FSD characterization (LaRue et al., 2022); however, a closer look at our data shows that REA of certain FSD metrics may be influenced by how the underlying lidar point cloud data are used in the derivation of those FSD metrics. Both CRR and FHD have relatively lower REA than other FSD metrics and are both calculated using canopy height return distribution based on all the lidar returns through the canopy, rather than just the ‘first returns’ as do many other FSD metrics. However, R_T , which is only based on ‘first returns’, also has a comparatively lower REA than CC or height metrics. Given the findings of LaRue et al. (2022) and the consistency we observe across the lidar sampling densities in our data, we interpret this not as being a sampling density issue, but rather evidence supporting the advantages of using complexity and arrangement metrics such as CRR, FHD and R_T in ecological research as they provide a more comprehensive, integrated picture of forest structure.

Leaf area, as we mention above, is a special case. We show that the REA for leaf area is relatively small and highly constrained in comparison to other structural variables. The most used estimates of leaf area are derived from passive remote sensing sources (e.g. Landsat, MODIS, terrestrial-based ceptometers, hemispherical photography); however, our findings on the REA for lidar-based estimates of leaf area do not necessarily translate to those passive remote sensing approaches. In addition, we employed a consistent coefficient within the MacArthur–Horn algorithm to approximate leaf area. Most often approaches to estimate leaf area from lidar are done at a spatial grain of less than 30 m and whether the assumptions regarding extinction coefficients at higher grain sizes hold is relatively unexplored and requires further investigation. More significantly however is the influence of large canopy gaps, occlusion and clumping effects. As voxel size increases, the likelihood of including larger canopy gaps increases, as does the difficulty in accounting for occlusion effects (Béland et al., 2014; Soma et al., 2018). To adequately characterize leaf area requires consideration of voxel size and algorithm selection (Kamoske et al., 2019; Weiss et al., 2004) and may be most

appropriately accomplished by first calculating leaf area at a 0.5–2 m spatial grain and then averaging up to coarser grains.

While there is evidence that the REA of FSD metrics differ by forest type, more work is necessary here for a robust treatment of this question. Our goal was to show the necessary REA to capture the magnitude and variability of different structural metrics within and across forest ecosystems. To adequately test differences in REA among forest types would require more data than presented here, though the differences we observed between leaf area, CC and forest height among mixed, needleleaf and broadleaf forests are consistent with previous findings (Atkins et al., 2022; Kamoske et al., 2019). Mechanistically, individual tree architecture (e.g. conical forms of many needleleaf trees; Ishii & Asano, 2010) and lidar sensor considerations (e.g. beam divergence and footprint size) interact to affect structural measurement in different systems (Fang et al., 2013; Tang et al., 2019).

Our findings show strong evidence that many if not all forest structural attributes can be estimated with a high degree of certainty from moderate spatial grain (25–75 m) as outlined above. Sensors such as GEDI, which provide ~25 m diameter, integrated waveform structural measurement (Dubayah et al., 2020), is likely sufficient to characterize forest structure within most forest ecosystems. We also propose for modelling studies integrating lidar-derived structural measurements that consideration be given to the grain size used if workers are aggregating data from raw point clouds. Consideration should also be given to matching grain sizes with sufficient REA to capture the structural attribute desired with the grain size of the target function or entity, otherwise scaling efforts will be misaligned or misinformed. For example, some small mammal or bird species rarely move or migrate beyond a small area (~100 m²) while other species such as large herbivores or predators may cover hundreds of square meters a day. If lidar-derived forest structural metrics are being employed to characterize habitats, a mismatch of grain sizes that do not adequately capture the magnitude and/or variability of structural attributes will potentially undermine any conservation efforts or research findings. The same consideration is necessary for the use of lidar in other contexts. Lidar data have extensive use in modelling many ecosystem functions, specifically carbon cycling processes (Xiao et al., 2019) such as above-ground biomass (Becknell et al., 2018; Cao et al., 2016; Fatoyinbo et al., 2018), productivity (Béland et al., 2019; Gough et al., 2019) and resource-use efficiencies (Hardiman et al., 2013). Greater consideration to scale dependency could constrain uncertainties and lead to greater confidence in how lidar data are used in these contexts.

Our findings indicate a need for researchers to consider grain, scale and extent when using lidar derived FSD metrics. Rarely are estimates of any forest structural attribute such as CC or canopy height made based on single observations, but rather based on the aggregation of multiple estimates, such as averaging across a canopy height model (CHM) to estimate mean forest height. The use of REA as a guiding heuristic allows for a standardized approach to address this need. For example, if the desired use case is to capture both the

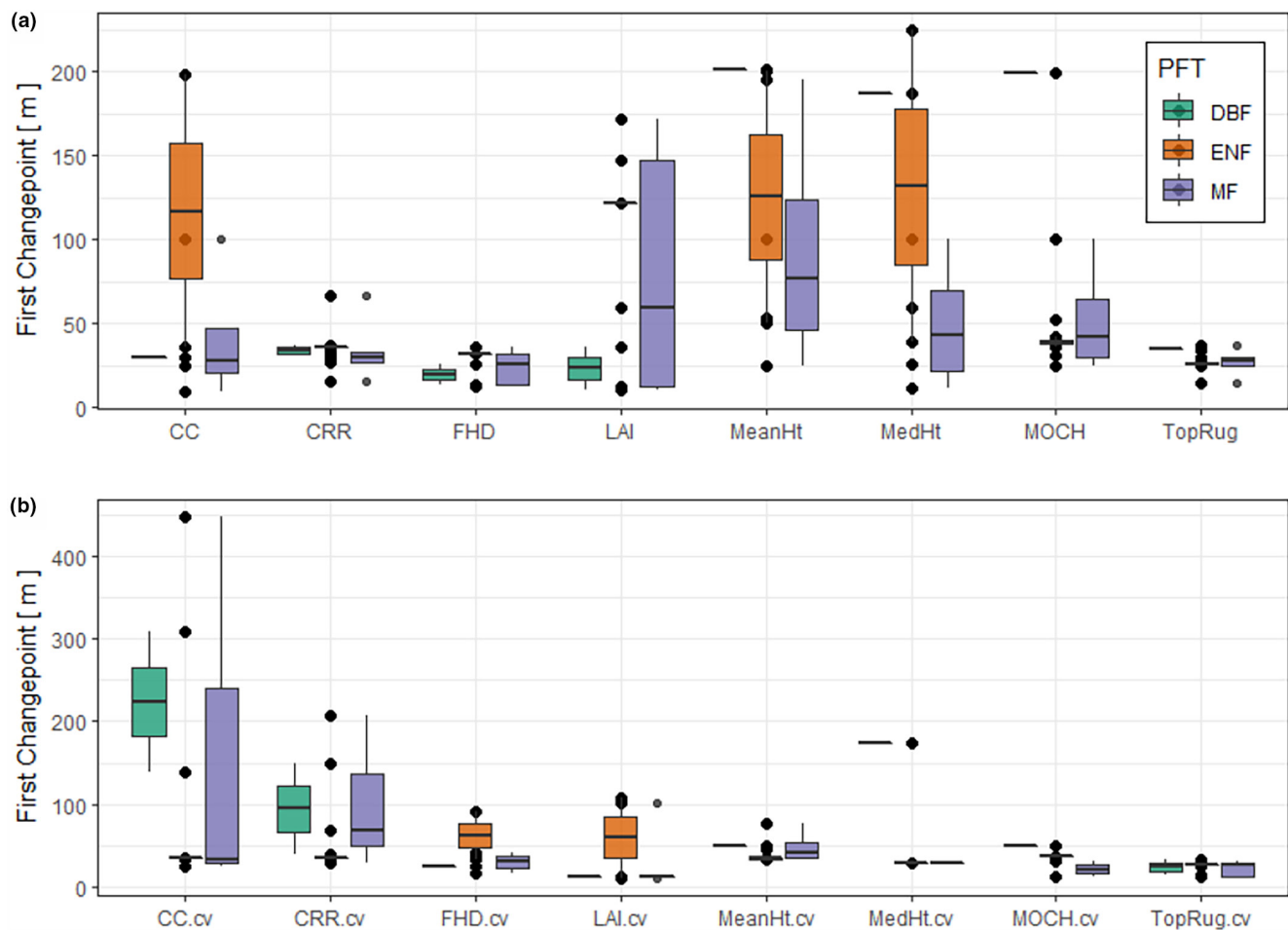


FIGURE 6 (a) Box plot depicting differences in statistically significant changepoints for the magnitude of each structural diversity metric by plant functional type or PFT where DBF is deciduous broadleaf, ENF is evergreen needleleaf forest and MF is mixed forest type (Bonan et al., 2002); (b) box plot in the same manner depicting coefficient of variation for each metric.

magnitude and variability of forest height, 40m may be an optimal grain size as it falls within the IQR for the magnitude of the median canopy height (H_{Median}) and MOCH and within the 10–25 percentile range of mean canopy height (H_{Mean}) and the range of the CV of mean and median height. CHMs are the most common tools for working with forest height data and are most often derived from the interpolation of top-of-the-canopy or outer canopy height, analogous to the structural metric MOCH—which has a similar REA to the median canopy height, however different than mean canopy height (H_{Mean}). A robust consideration herein of what is meant by the term ‘forest’ or ‘canopy height’ is outside of the scope of this research, yet our findings indicate that such a robust examination, both from a statistical and theoretical stance, is necessary.

This work could inform how FSD metrics are used more broadly, specifically in fusing lidar data with additional information. If we consider the example of predicting species occupancy with lidar-derived FSD measurements, we can see how the REA concept informs such data fusion approaches. The presence/absence or movement of different species can be acquired many ways such as the use of GPS tracking for larger animals (e.g. deer, hogs, wolves) or via point counts for smaller animals (e.g. rodents, birds). GPS tracking

approaches carry a measurement error on the order of 1 s or 10s of meters and may provide about 1–3 data points a day telemetry-based methods provide similar location accuracies (Kilgo et al., 2021) but more frequent sampling. When animal movement data are combined with remote sensing data such as Landsat or MODIS, the standard operating procedure is to aggregate to the native resolution of the remote sensing data (e.g. 30m for Landsat or 250m for MODIS). The use of lidar data however allows for finer spatial resolution analysis than either Landsat or MODIS, providing the user the option to ‘define’ the scale of ‘interest’ as they see fit. The use of REA defined scale thus could provide guidance on the appropriate scale regarding how lidar-derived FSD metrics could be incorporated into these models more robustly. Similarly, an REA-based approach could inform the analysis and scaling of ecosystem services, habitat characterization and biogeochemical modelling.

5 | CONCLUSIONS

Here we estimate the REA of lidar-derived structural metrics for several forest types in the United States allowing us to quantify the

spatial grain size necessary to capture the magnitude and variability of FSD. There are observed differences among metrics of different forest structural categories in the REA necessary for adequate characterization, but spatial grain sizes of 25–75 m are generally sufficient for most sites and structural metrics. Determining the appropriate spatial grain size of lidar-derived forest structural metrics could allow more mechanistically sound and targeted use of lidar data that balances the needs of the scientific application with the pragmatic considerations inherent in all remote sensing (e.g. trade-offs between resolution and level of detail). While our findings may not be a universal fit for all systems or all studies, the approaches we have employed are and could be used for systems not included in this analysis.

Our findings provide guidance on how lidar-derived FSD metrics may be implemented in ecological, biological, and conservation research and management by providing statistical underpinning to their calculation. Given the absence of a native spatial grain in lidar point cloud data, the use of an REA-based approach to FSD calculation represents an improvement over the current ad hoc approach of aggregation based solely on the process of interest. Considering both the appropriate scale of the FSD metric(s) in addition to the scale of the process(es) of interest will increase our confidence in the conclusions and inferences drawn from studies that employ FSD metrics.

AUTHOR CONTRIBUTIONS

All authors contributed to the intellectual development and conception of this manuscript; Jeff W. Atkins, Kyla M. Dahlin, Brady S. Hardiman, Elizabeth A. LaRue and Elske K. Tielens participated in the NSF workshop leading to the creation of this manuscript with all authors contributing to follow-up discussion regarding this manuscript; Jeff W. Atkins, Christopher R. Hakkenberg, Brady S. Hardiman and Elske K. Tielens collaborated on the original draft; Jeff W. Atkins performed the analyses with support from Christopher R. Hakkenberg, Andrew J. Elmore, Aaron Kamoske and Matthew C. Fitzpatrick; all authors contributed to revisions.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1111/2041-210X.14040>.

DATA AVAILABILITY STATEMENT

All analysis scripts have been made available via a GitHub repository: https://github.com/atkinsjeff/lidar_scaling_analysis. Summary data are available in [Supplementary Information](#).

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