9-6-2023

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Received: 15 November 2022 | Revised: 18 May 2023 | Accepted: 30 May 2023

DOI: 10.1002/ecs2.4633

ECOSPHERE
AN ESA OPEN ACCESS JOURNAL

ARTICLE

Methods, Tools, and Technologies

Integrating forest structural diversity measurement into ecological research

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Abstract

The measurement of forest structure has evolved steadily due to advances in technology, methodology, and theory. Such advances have greatly increased

Funding information
National Science Foundation (NSF), Grant/Award Number: 1924942

Handling Editor: Charles D. Canham

our capacity to describe key forest structural elements and resulted in a range of measurement approaches from traditional analog tools such as measurement tapes to highly derived and computationally intensive methods such as advanced remote sensing tools (e.g., lidar, radar). This assortment of measurement approaches results in structural metrics unique to each method, with the caveat that metrics may be biased or constrained by the measurement approach taken. While forest structural diversity (FSD) metrics foster novel research opportunities, understanding how they are measured or derived, limitations of the measurement approach taken, as well as their biological interpretation is crucial for proper application. We review the measurement of forest structure and structural diversity—an umbrella term that includes quantification of the distribution of functional and biotic components of forests. We consider how and where these approaches can be used, the role of technology in measuring structure, how measurement impacts extend beyond research, and current limitations and potential opportunities for future research.

KEYWORDS
forest ecology, forest structure, forestry, landscape ecology, lidar, measurement, remote sensing, spatial sampling, structural diversity

INTRODUCTION

Our ability to measure forest structure has greatly progressed in recent years due to technological and theoretical breakthroughs, primarily in the field of remote sensing, which have provided the long-awaited capability to precisely measure multiple dimensions of forest structure across resolutions and over vast extents. The broad availability of a suite of accessible tools and approaches to measure forest structural diversity (FSD) has fostered with novel opportunities to integrate FSD into research. Previously, the use of many remote sensing tools and associated data products have been restricted to only the most resource-rich or tech-savvy individuals, limiting the impact of such advancements. However, we are now on the precipice of broad inclusion of tools such as terrestrial lidar scanners (TLS), unoccupied aerial vehicles/systems (UAV/UAS), and radar for ecological research. While this portends the possibility of exciting, transformative research, understanding the basics of how forest structure and structural diversity can be quantified via remote sensing can guide research applications. Here we present a review and introduction to how these new technologies can be integrated into ecological research.

Forest structure and forest structural diversity

Broadly, forest structure refers to the distribution of individual trees or biomass in space within a forest (Goff & Zedler, 1968; Zenner et al., 2012); FSD specifically refers to the patterns of these distributions (LaRue et al., 2023; McRoberts et al., 2008), or more precisely, the multidimensional characterization of measurable forest structural attributes including stand structure, height, cover, volume, heterogeneity, arrangement, and the distribution of functional and biotic components (Hakkenberg & Goetz, 2021; LaRue et al., 2023). Accordingly, FSD measurement has broad implications for science, policy, and management (Beland et al., 2019; Eitel et al., 2016; Kruys et al., 2013; Meng et al., 2016). Accurate and precise quantification of FSD is necessary for understanding environmental drivers of community organization and composition (Hakkenberg et al., 2018; Heidrich et al., 2020) including species presence, abundance, and distribution (Borcard et al., 1992; Vihervaara et al., 2015); sustainable forest management, wildlife conservation, and restoration initiatives (Almeida, Stark, et al., 2019; Garabedian et al., 2017; McNeil et al., 2023; Parker & Russ, 2004; Valbuena et al., 2020; Wales et al., 2020); detecting forest disturbance (Atkins et al., 2019; Jucker, 2021; Zhai et al., 2022) and system recovery (Almeida et al., 2021; Meng et al., 2018); characterizing habitat (Hernando et al., 2012) and microclimates (Ehbrecht et al., 2017; Zellweger et al., 2020) and mapping land cover change (Erb et al., 2018).

Outside of the field of applied forestry, the study of forest structure has historically focused on tree species composition and abundance, with limited emphasis on physical structure—despite the recognized potential importance of structure to ecological pattern and process

(Long & Shaw, 2009; Shugart et al., 2010; Wiens, 1974). The key contributors to this oversight have been the logistical, theoretical, financial, and technological constraints on measuring the physical structure. Advances in technology and theory have expanded our ability to measure FSD; however, the application of FSD measurements in ecological research relies on understanding the range of available FSD metrics, how they are derived, their biological interpretation, and their potential applications and limitations. To be broadly useful, any measures of FSD should be temporally sensitive and complementary to compositional measures (Proença et al., 2017) and serve as reliable proxies for predicting stand- to global-scale biodiversity (Cavender-Bares et al., 2020; Jetz et al., 2019) and functional diversity (Asner et al., 2017). Here, we review: (1) the range of available FSD metrics and the structural attributes they assess; (2) how FSD measurements are derived; (3) considerations for the application of FSD in research and applications; (4) implications of the use of FSD for science, policy, and management; and (5) current limitations and potential future directions.

STRUCTURAL ATTRIBUTES MEASURED BY FSD METRICS

There are several structural attributes of forests that may be quantified using FSD metrics, which we have grouped as: *stand structure* (e.g., tree size and stem diameter distributions, trees per acre, canopy volume); *height, cover, and openness* (e.g., gap fraction, canopy cover); *heterogeneity* (also vertical stratification or canopy structural complexity); *vegetation area and density* (e.g., leaf area index); and *structural heterogeneity of traits or taxa* (e.g., diversity/distribution of foliar traits; Fahey et al., 2019; Matasci et al., 2018; Sheldon et al., 2006) (Figure 1; full descriptions in Table 1).

FSD measurements most often are distilled down to singular metrics describing specific structural attributes of forests. Metrics may range in their level of complexity from the straightforward such as stand density—the number of trees for a given area (e.g., trees per acre or trees per hectare)—to highly derived metrics such as foliage height diversity—the distribution of canopy layers within the vertical plane. Distillation is a key advantage of FSD metrics, facilitating extensive spatially explicit datasets to be condensed or aggregated down to a single, information-rich metric or metrics that can then be used in modeling or analysis efforts. The range of complexity of FSD metrics is based on the dimensionality of the metric, data needed for calculation, and the level of processing or derivation required (Table 1). The choice of which FSD metric(s) to use for a given application should be informed by: (1) the structural attributes under investigation; (2) spatial and temporal resolution and extent based on the scale of the system of study; and (3) the ability to obtain, access, process, and analyze the necessary data.

FSD measurement

The structural attributes of forests quantified by FSD metrics can be measured via multiple approaches, platforms, and methods. While a complete, detailed understanding of each method of measurement and its associated nuances may be unnecessary for many practicing ecologists and researchers, a cursory understanding of how FSD measurements are made is beneficial. FSD measurement is influenced by several technological or theoretical factors—measurement precision, instrument resolution and extent in both time and space, speed and ease of measurement acquisition, logistics of data acquisition and storage, ease of data usage, access to software and tools to work with data, and the existence of pipelines for processing and analyzing data. To discuss these points in further detail, we have chosen to group our discussion by traditional field-based methods and by remote-sensing-based approaches.

Traditional field-based approaches

Forestry has always been a field of measurement. The need for sustainable timber production necessitated the rise of forest management practices underpinned by standardized data on the abundance, volume, and distribution of trees to meet this need (Avery & Burkhart, 2015). This led to the rise of the subdiscipline of forest mensuration, which is focused solely on the measurement of forests and forest structure. Technology evolved over time to meet these needs, giving us tools such as dbh tapes, relascopes, clinometers, calipers, the Biltmore stick, and methodologies such as allometries and yield tables. Traditional methods capture several, but not all, forest structural attributes listed above (i.e., stand structure, height, vegetation area and density, and volume and surface area).

Traditional methods are often individual-, point-, or plot-based (e.g., forest inventory plot, common stand exam) and require extensive time and financial investment to acquire new data. This results in workforce capacity—either in the form of time or money or both—as the primary limiting factor on data acquisition via traditional methods. These logistical constraints result in fewer samples, coarser grains, and/or smaller spatial extents than many remote sensing approaches (Figure 2).

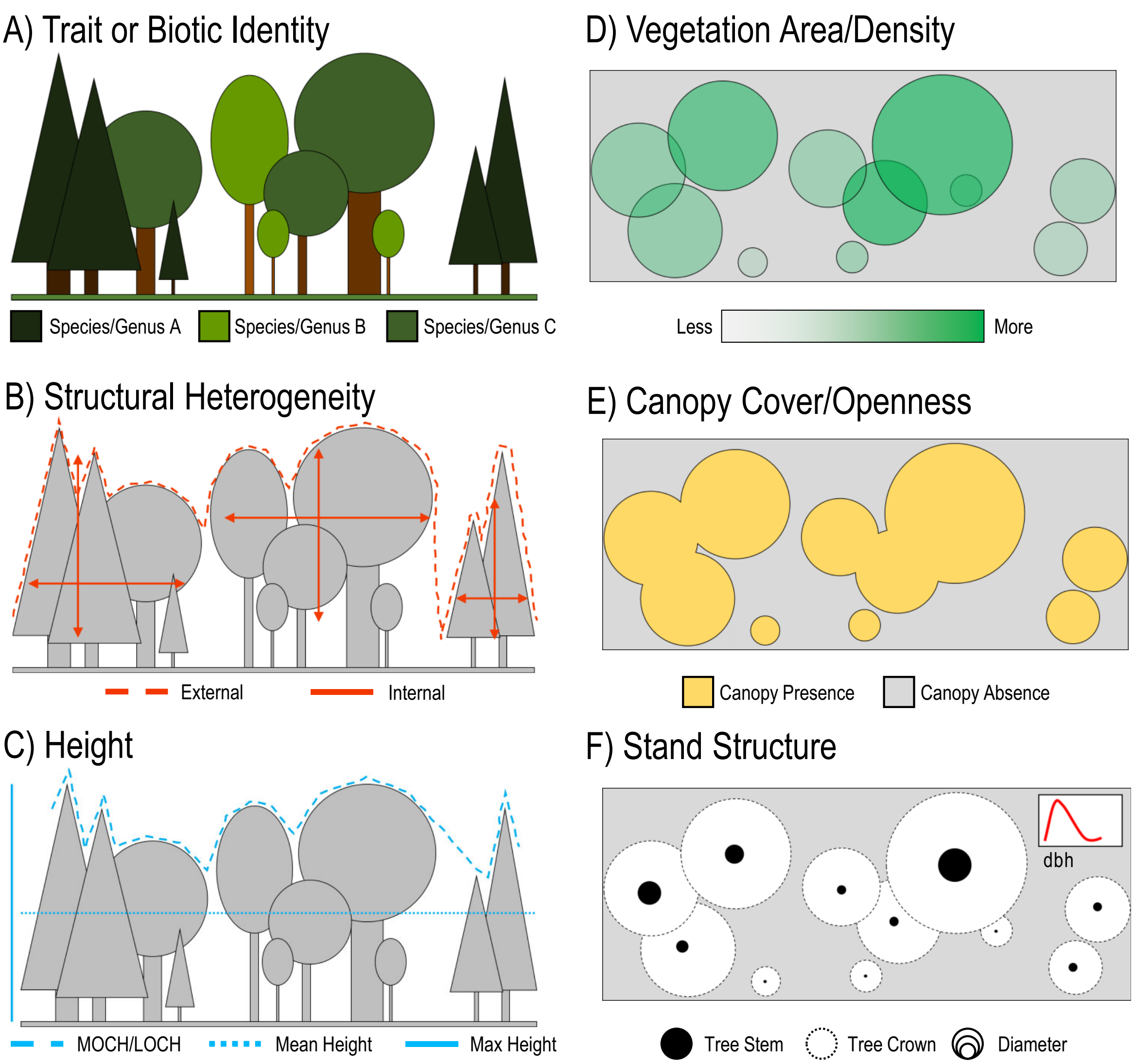

FIGURE 1 Conceptual diagrams of structural attributes (Table 1). (A) Three tree species distinguished by color but could also represent some trait (e.g., nitrogen content); (B) internal and external structural heterogeneity, based on the arrangement of all vegetated elements in 3D space; (C) three measures of canopy height including mean outer canopy height (MOCH) or local outer canopy height (LOCH), mean canopy height, and maximum canopy height; (D) shown in overhead 2D, the darker colors indicate greater leaf area/density; (E) canopy cover shown as absence or presence; (F) stem distribution map showing relative dbh based on size of circle as well as a dbh distribution curve at top right.

However traditional measurement does provide granular information at the level of the individual that is not possible with many remote sensors, creating a trade-off in extent versus resolution and precision versus accuracy. dbh, for example, is mostly measured using calibrated measurement tapes (dbh tapes) or calipers, each with a typical precision of 0.1 cm and associated measurement error of ±0.2–0.5 cm (Luoma et al., 2017). Tree height can be measured using a standard transect tape with either a clinometer or hypsometer coupled with basic trigonometry, with precision ranging from 0.1 to 1 m and associated measurement error up to ±10% (Andersen et al., 2006; Luoma et al., 2017). Other FSD attributes such as basal area or volume can be measured using basal area prisms or tools such as a Biltmore stick (Hovind & Rieck, 1961), tools calibrated to give direct estimates of these variables as opposed to estimates scaled up from dbh tapes using allometries (Jenkins et al., 2003). First-order measurements taken via traditional measurements (e.g., diameter, height, distributions) can be used to calculate advanced second-order metrics invaluable in both forestry and ecology (e.g., dissimilarity indexes, site index).

One of the key major advantages of traditional FSD measurement approaches is the lower investment costs in both time and money in data processing and analysis. FSD data acquired via traditional methods (e.g., dbh, basal area, tree height) tend to be intuitive and readily analyzable via standard database and spreadsheet software environments. However, this ease of use does not

TABLE 1 Categories of structural attributes with accompanying information, including detailed descriptions of each attribute, dimensions of the associated data, and example metrics and approaches toward quantification.

Structural attribute	Description	Data dimensions	Example metrics	Measurement approaches
Stand structure	Distribution of tree size or tree stem diameters, including basal area and tree volume	1D, 2D, 3D	Variance in diameter distributions, Gini coefficient, Weibull profile, power function scaling exponent, stand density, stand volume, board feet, fractal geometry, and ecosystem volume	Standard forestry methods include dbh tapes, Biltmore sticks, relascopes, angle gauges, etc. Remote sensing methods include terrestrial laser scanning or inference from aerial lidar or orthoimagery via statistical means (e.g., crown segmentation, imputation). Additionally volume from allometries and yield tables (e.g., stand volume, board feet). Require a low to high level of processing complexity.
Height	Tree or vegetation height, as well as height profiles, from ground to emergent canopy and aggregated height (e.g., mean, median, or local outer height)	1D, 2D, 3D	Lorey's height, mean outer canopy height, vegetation height percentile distribution, canopy relief ratio, and vertical distribution index	Traditional methods include hypsometers, relascopes, and clinometers. Remote sensing approaches include structure-from-motion, lidar, radar, and microwave. Height metrics vary from low to medium complexity processing levels.
Cover and openness	Relative proportion of canopy versus exposed forest floor	2D, 3D	Gap fraction and canopy cover	Hemispherical imagery, orthoimagery, and lidar. Cover and openness vary from low to medium processing.
Heterogeneity/ vertical stratification/ canopy structural complexity	Variation in the 3D arrangement of canopy elements	3D	Rumple, rugosity, foliage height diversity (FHD), and structural complexity index (SCI)	Currently only estimated from terrestrial, aerial lidar, and spaceborne lidar and tend to require a high level of processing complexity.
Vegetation area and density	The no. and density of vegetation surface layers	2D, 3D	Vegetation area index (VAI), effective no. layers (ENL), leaf area density (LAD), porosity, leaf area index (LAI), wood area index, and plant area index	Orthoimagery, hemispherical imagery, lidar, radar—though ENL and porosity are only from aerial and terrestrial lidar currently. These metrics require a medium to high level of processing complexity.
Structural heterogeneity of traits or biotic identity	Variation in the 3D arrangement of functional or biotic elements	2D, 3D	Height heterogeneity of different species, foliar or spectral diversity	Typically can only be inferred statistically from other stand structural data or via integration of structural data with trait or other data and require a high level of processing.

belie their utility. Detailed information acquired from forest inventory plots or common stand exams has been and will continue to be vital to research. Additionally, since traditional methods are well established within the research and management communities, they tend to be available for a broad range of systems and forests and are well established in the literature.

FSD measurement via remote sensing

While transformative to how we study forests and the Earth system, FSD measurement via remote sensing also carries specific advantages, considerations, and limitations regarding its use. The remote sensing platforms available for measuring FSD range from small handheld

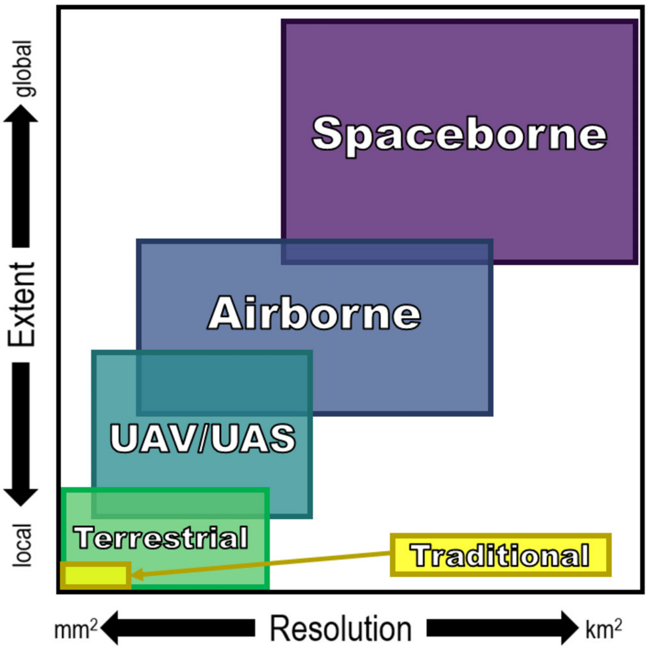

FIGURE 2 Sensors and tools used to make forest structural diversity measurements vary in the spatial extent or resolution at which they can provide continuous structural information. Spaceborne instruments may provide near-global coverage but lack fine-scale spatial resolution; terrestrial-based instrumentation or traditional forestry tools might provide fine-scale, highly precise information at the local scale but require far too much time and effort for broader coverage. Unoccupied aerial vehicles/systems (UAV/UAS) and airborne platforms provide information at moderate resolution and extent.

devices (e.g., personal mobile device) to spaceborne platforms (Figure 2). The spatial extent and grain of a given sensor inherently influences the types of structural features it can quantify and determines the accuracy and precision of which it is capable (Atkins et al., 2023; Saatchi et al., 2011).

Broadly there are two types of remote sensing, passive and active. Passive remote sensing relies on recording energy (i.e., radiation) reflected or emitted from an object illuminated by an external energy source, most often the Sun. Recorded energy is measured as reflectance—the ratio of the amount of energy emitted from a target to the amount of energy striking that target. Passive remote sensing is an important tool, but it is not capable of directly estimating forest structure because light is scattered within a forest canopy, which affects the measurement of spectral response by confounding the relationship between the signal and any leaf or canopy-level scattering properties (Knyazikhin et al., 2013). Reflectance data are used to predict chemical (e.g., leaf nitrogen content) and functional (e.g., phenology, evapotranspiration) ecosystem properties and are used to calculate spectral indices—ratios of one or more spectral bands to another—which are important for everything from estimating plant stress to tracking deforestation. There are more than a hundred ecologically relevant spectral indices (Kriegler et al., 1969; Xue & Su, 2017; Zeng et al., 2022) with broad applications. While many structural attributes of forests cannot be directly estimated from reflectance data without unconstrained error (Fisher et al., 2018; LaRue et al., 2019; Zeng et al., 2022), passive remote sensing is vital in ecological research to determine forest cover classifications based on vegetation composition and community dominance (Bhatt et al., 2022; Wulder et al., 2004); and to estimate crown closure and crown gaps (Frolking et al., 2009; Wang et al., 2004); aboveground forest biomass (Yan et al., 2015); and stand structure (e.g., leaf area, stem density, height, volume, and basal area), stand maturity (Cohen & Goward, 2004), and successional stage (Hall et al., 1991; Song & Woodcock, 2002). Spectral variation can even be used as a proxy for species richness (see spectral variation hypothesis; Rocchini et al., 2004; Schmidtlein & Fassnacht, 2017) and function (Schweiger et al., 2018).

Active remote sensing surmounts many of the limitations of passive systems by recording how emitted energy interacts with the environment without the confounding influence of an external radiation source, providing direct estimation of FSD (Coops et al., 2021; Lefsky et al., 2002). Active remote sensing such as lidar sensors measure the time required for an emitted light pulse to intercept an object and return to the instrument. Given the speed of light is constant and the known sensor position and beam trajectory, relative distances from objects to the sensor can be calculated directly. In forest applications, lidar produces a three-dimensional characterization of the forest as either discrete points (e.g., point clouds) in the case of time-of-flight measurement, or as a continuous waveform in the case of waveform lidar. While several sensor-specific attributes constrain or bias measurement (e.g., laser beam spot size, beam divergence, pulse density, system range, and the speed with which the sensor motor spins), lidar-based estimates of forest structure have been found to excel in terms of precision, accuracy, consistency, and spatial extent (Coops et al., 2021), making lidar the leading tool in FSD measurement for the foreseeable future.

Radar and microwave remote sensing rely on sensing objects roughly larger than the wavelength of the emitted signal (Henderson & Lewis, 1998). As a result, many radar bands can pass through cloud cover and long wavelength bands (e.g., P band), can even pass through fine vegetation elements (Imhoff, 1995). Radar backscatter largely reflects water distributed in a mixture of soil and vegetation properties, thereby capturing forest structure. Vegetation parameters, including some structural properties (e.g., vegetation height, shape, and orientation of plant elements), can be retrieved from radar data using a model inversion approach that employs a specific discrete model based on radar polarimetry, but is most applicable in lower density forests before reaching the "saturation" point (Joshi et al., 2017), beyond which return energy does not vary with increasing biomass. For stands with higher density, the performance of radar is often poor because the sensitivity of backscatter to forest structural properties decreases dramatically (Saatchi et al., 2011). Microwave bands (C and X bands) can penetrate rather deeply into the forest canopy, potentially providing a more detailed characterization of internal canopy structure than air- or spaceborne lidar, avoiding signal interference from occlusion (Disney et al., 2006). Microwave bands are also sensitive to changes in foliage and leaf area (Du et al., 2019), and to moisture content, indicating the ability to provide robust estimates of leaf area (Tanase et al., 2019).

Close-range or proximal instruments such as TLS (Calders et al., 2020), mobile phones (Tatsumi et al., 2022), photogrammatry (Mokroš et al., 2018) and tripod-based instruments are capable of mm- to cm-scale spatial resolution and precision, making it possible to collect information on individual leaves/needles, stems, branches, boughs, and trunks (Moorthy et al., 2019). TLS has been found effective in estimating biomass (Calders et al., 2015; Wilkes et al., 2018), forest function (Atkins et al., 2018; Fotis, Morin, et al., 2018; Fotis, Murphy, et al., 2018), species habitat (Blakey et al., 2017), and canopy structure (Ehbrecht et al., 2016; Fahey et al., 2019; Walter et al., 2021). 3D point clouds can be processed using algorithms to identify points that belong to the same individual tree and geometric shapes can be fitted to the points to model individual structural elements within each tree (Disney et al., 2018; Raumonen et al., 2013; Stovall & Shugart, 2018; Wilkes et al., 2017). Close-range and proximal instruments offer highly resolved data that is not possible with other approaches to FSD measurement. However, adopting close-range and proximal instruments to measure FSD comes with a trade-off, either in the ability to gather detailed information for a single tree or structural variability across several trees, or in how much area can be sampled—as proximal sensors can only sample a small spatial extent (10s–100s of m^{-2}) due to data collection times and necessary computational resources (Wilkes et al., 2017).

UAV/UAS-based sensors can outpace both satellite and piloted platforms with ultrahigh horizontal and vertical resolutions as well as shorter time between visits (Singh & Frazier, 2018). UAV imagery is less affected by the atmosphere given the proximity between the sensor and the Earth surface—beneath the cloud layer. Flexibility across different applications and decreasing platform costs are at least partly responsible for the increasing adoption of UAVs (Tang & Shao, 2015). Significant advancements have been made in recent years in the use of UAV platforms for forest structural assessments (Almeida et al., 2021; Almeida, Broadbent, et al., 2019). Standards need to be determined on acceptable horizontal and vertical resolutions, flight altitudes, minimum imagery overlap, placement and number of ground control or reference points, optimal flight times with respect to solar elevation angle, photogrammetric processing methods, data reporting, metadata archival, and appropriate minimum mapping units, particularly for using UAV-based lidar for FSD measurement (Jozkow et al., 2016; Pádua et al., 2017; Petrie, 2013).

Airborne remote sensing platforms cover a greater spatial extent than either terrestrial or UAV/UAS platforms, but at lower spatial resolution due to factors like flying altitude and speed. The small-footprint sampling of airborne platforms (i.e., several laser pulses per square meter) is suitable for measuring vegetation clumping, canopy gaps, and individual tree properties. Models of canopy height, shape, roughness, fractional cover, biomass, and other structural properties can be generated from aerial lidar at the spatial grain of interest for a given ecosystem function or structural property. 3D point clouds can also be used to analyze canopy layering or stratification between understory, mid-story, and upper canopy vegetation, and describe the horizontal and vertical variability in vegetation structure among individuals across the landscape (Jung et al., 2013; Whitehurst et al., 2013). Canopy height profiles generated from airborne lidar have been shown to describe the vertical distribution of canopy structure and correlate with forest age and composition (Hakkenberg et al., 2018), and they can also be used to characterize floristic diversity (Cavender-Bares et al., 2020; Hakkenberg & Goetz, 2021). Individual tree detection (ITD) and crown segmentation algorithms are advanced computational approaches that allow for quantifying FSD at the individual tree level from lidar point clouds or canopy height models (Silva et al., 2022; Valbuena et al., 2014) and are useful for estimating biophysical parameters such as biomass, volume, and canopy cover (Silva et al., 2016; Stark et al., 2012).

Spaceborne lidar sensors such as GEDI, a full-waveform lidar sensor with a 25-m ground-level footprint, and ICESat-2, a photon-counting lidar sensor with a 10-m ground-level footprint, provide 10-return data at approximately the same scale as typical field-sampling plots (Abdalati et al., 2010). Several trees are combined within a footprint and differences in structure in the horizontal dimension are lost. Canopy height, canopy cover, and vertical layering can also be analyzed. Using lidar data with radiative transfer models allows for the extraction of more advanced structural information such as vertical optical gap probability and vertical leaf area density. Spaceborne lidar missions achieve near-global coverage but do not have the wall-to-wall sampling that is common from airborne systems, with small gaps between sequential laser pulses (60 m for GEDI) and larger gaps between laser ground tracks (600 m for GEDI) (Dubayah et al., 2020), but interpolation methods based on fusion with ancillary datasets like Landsat (Li et al., 2020; Narine et al., 2019; Potapov et al., 2020) or TanDEM-X (Qi et al., 2019; Stovall et al., 2020) are enabling high-resolution wall-to-wall maps of forest structure (Hakkenberg et al., 2023; Lang et al., 2022; Wang et al., 2022).

Spaceborne sensors have a large extent, but coarse resolution, and are therefore more applicable at regional (Smart et al., 2012) or global (Tang et al., 2019) scales; FSD measurements derived from such sensors are a reliable surrogate for other branches of biodiversity (e.g., taxonomic, trait, or phylogenetic) while capturing the variability of diversity among multiple taxa (Pommerening, 2002). Attributed to faster return rate of some orbiting satellites (MODIS Terra and Aqua), temporally sensitive FSD measurements (e.g., greenness for phenology) can be derived from such spaceborne sensors. Consequently, these FSD measurements can help researchers understand successional dynamics, impacts of disturbances, community/ecosystem resilience, post-perturbation community recovery, and unravel landscape patterns and habitat connectivity (Francis et al., 2023; Garabedian et al., 2017; Newman, 2019; Newman et al., 2019; Possingham et al., 2005; Romme, 2005).

Considerations for using remote sensing for FSD measurement

The diverse array of remote sensing approaches leads to data products that vary in spatial and temporal extent. There are inherent trade-offs in spatial extent versus spatial resolution for remote sensing approaches—large spatial extents, coarse resolution from by air- and spaceborne remote sensing versus small extent, very fine spatial resolution from proximal remote sensing (Figures 2 and 3). Several factors constrain the trade-off between spatial resolution and extent including sensor specifications and signal-to-noise ratio, sensor altitude, uncertainty in geolocation, sensor pointing precision, as well as signal attenuation and ground finding issues in dense canopies. Proximal remote sensing instruments such as TLS or UAV-based systems are expensive, with high instrument costs ranging into 100s of thousands of USD, along with subsequent high costs for proprietary software licenses. Most air- and spaceborne remote sensing platforms are far too expensive for a singular lab or research group to afford and are typically supported by for-profit companies, research networks, federal agencies, countries, or consortiums. While data generated from platforms owned by for-profit companies (e.g., Planet Labs) require purchase, data from platforms owned or operated by other means tend to be publicly available (e.g., Landsat, MODIS, GEDI). Thus, the use of remote sensing for research relies heavily on large grants or existing publicly available data. Another consideration with the use of remote sensing data is the necessity for specialized training and software. Software environments for working with remote sensing data require a significant investment in training, whether it be for proprietary (e.g., ENVI, ArcGIS) or open-source solutions (e.g., Google Earth Engine, R, Python). Remote sensing work often requires more advanced computing solutions, though cloud computing services (e.g., Google Earth Engine, Jupyter Notebooks) are helping address this issue.

SCIENCE, POLICY, AND MANAGEMENT IMPLICATIONS

FSD measurement has profound implications beyond research, extending into social, political, and economic spheres. Standardized FSD measurement could strengthen environmental policies and be used to assess progress toward achieving biodiversity, climate, and natural resource management goals (Jetz et al., 2019) and forest structure–wildlife fitness relationships to guide endangered species recovery (Garabedian et al., 2021). Increasing the availability, consistency, and utility of FSD measurements for compliance with forest carbon offset programs (e.g., California's forest carbon offset program) can further bolster the effectiveness of policy implementation and help scientifically informed, data-driven policy reforms. For instance, FSD measurements could be integrated directly as essential biodiversity variables (EBV) or indirectly used as environmental predictors of species distributions through occupancy modeling or ecological niche modeling (Jetz et al., 2019). FSD metrics yield information on the status and trends in key biodiversity targets, which then can be used to gauge the impacts of international treaties (e.g., Convention of Biological Diversity) that strive toward biodiversity conservation targets like the UN's Sustainable Development Goals. One necessary step toward the integration of FSD into research and management is to increase the availability and visibility of FSD data. Such precedents exist. The

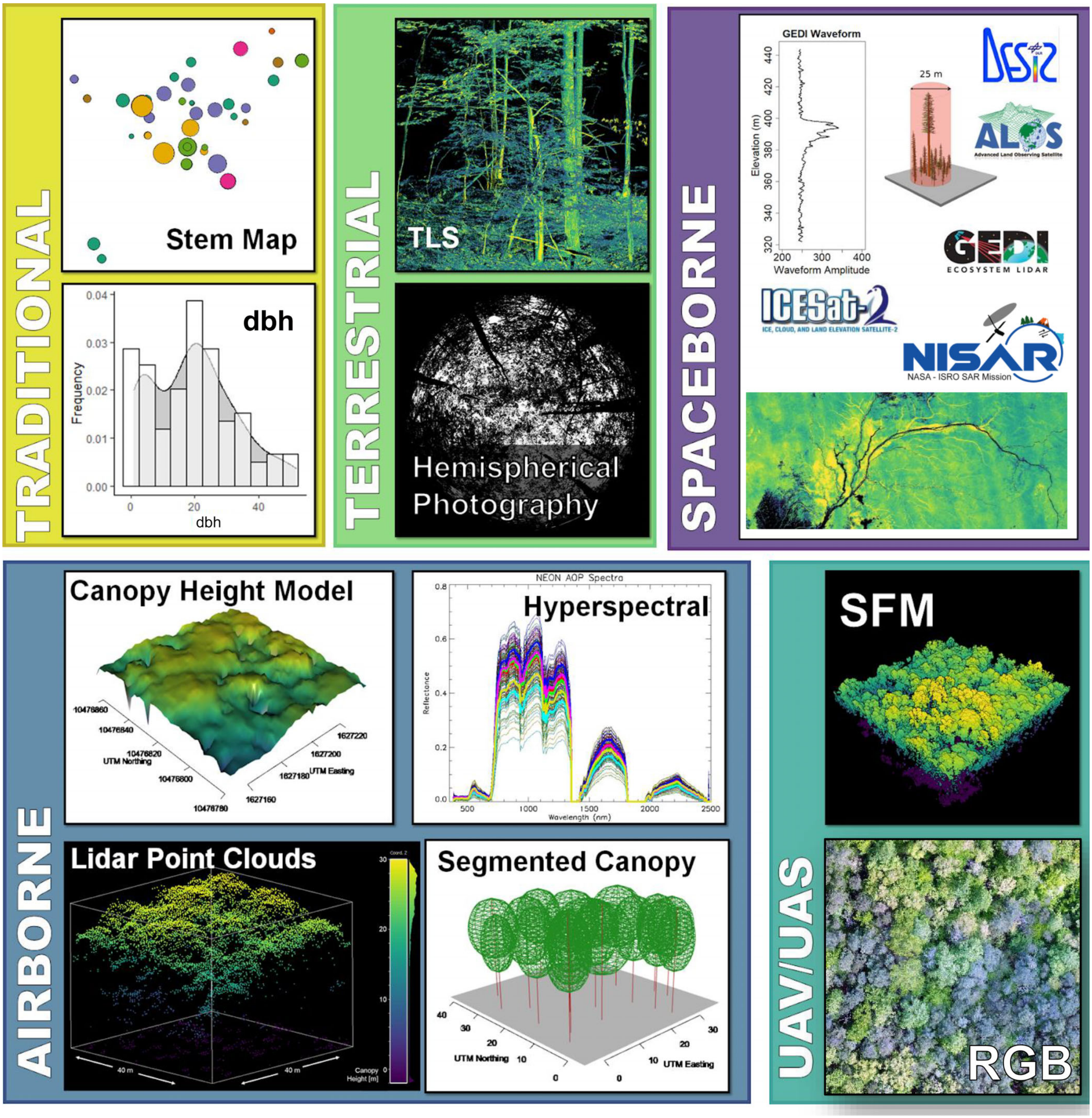

FIGURE 3 Graphical depictions of real data taken from many different platforms, perspectives, and sensors used in forest structural diversity metric calculation. Traditional measurements of dbh (dbh tape) and stem locations (compass and transect tape) used to make stem maps and tree size distributions (data from Harvard Forest, NEON plot HARV_036; NEON, 2022a). Terrestrial measurements of canopy structure from a 3D terrestrial lidar scanner and hemispherical camera (FoRTE Project, University of Michigan Biological Station; Atkins et al., 2021). Spaceborne data examples including a GEDI waveform (HARV_036; Dubayah et al., 2020) and backscatter from synthetic aperture radar (African mangrove; ALOS PALSAR; Shimada et al., 2014). Airborne data showing a canopy height model, point cloud, and segmented forest canopy (HARV_036; NEON, 2022b) and hyperspectral signature (HARV_036; NEON, 2023), all from NEON AOP data. UAV structure-from-motion point cloud (Pace Estate; A. Stovall) and RGB orthoimagery (Pace Estate, VA; Atkins et al., 2020).

Landsat Archive, made available freely and openly by the United States Geological Survey (USGS), has profoundly enabled our ability to understand global ecosystem dynamics (Cohen & Goward, 2004; Wulder et al., 2012). Related progress whereby more FSD data are made available (e.g., National Ecological Observatory Network–NEON), as well as the tools and training to work with those data, could create a similar data revolution.

Robust FSD measurements that effectively capture changes in the 3D structure of forests beyond gross biomass assessments—such as forest regeneration, reforestation, degradation, deforestation, plant invasions, forest maturity, and successional stages, as well as tree size classes and differentiation between biomass sources (above/belowground, deciduous/coniferous, woody/non-woody)—can also help implement and sustain international policies geared toward greenhouse gas reductions, such as REDD+. Defensible measurement of forest carbon is one of the major challenges of carbon accounting (Badgley et al., 2021) and, therefore, is a potential barrier to more widespread implementation of forest carbon offset programs. Airborne-, satellite-, and UAV-based lidar could address some of the challenges in monitoring carbon for forest offset programs and increase the accuracy of carbon monitoring, helping to address bias created by scaling point measurements to landscapes (Disney et al., 2019; Marvin et al., 2014; Muller-Landau, 2009; Stovall & Shugart, 2018).

CURRENT LIMITATIONS AND POTENTIAL FUTURE DIRECTIONS OF FSD MEASUREMENT

A century or more of advancement in theory and instrumentation has generated a remarkable array of ecologically meaningful FSD measurements, yet there remain key gaps in our current ability to measure FSD, namely sufficient data collection and the ability to fuse traditional and remote sensing approaches, a need for robust theory underpinning FSD measurement and applications, standardized methodologies for deriving FSD, robust comparisons of FSD derivation and the underlying statistics and assumptions being made, approaches to intercomparison and scaling, technological constraints, data availability, and the ability to acquire and process data.

There is a need for high-quality, high-density data for the entire globe. However, perhaps even more important is the need to formulate novel, reproducible analytical approaches to accommodate comparisons among existing and future data products that vary in spatial, temporal, and spectral resolution to ensure backward compatibility when detecting temporal trends of FSD. The same challenge manifests at larger spatial extents, such as latitudinal or cross-continental comparisons of FSD that may require integration of spatially extensive remote sensing data of variable quality, collected from differential sensors or platforms into comparable measurement standards (Valbuena et al., 2020). Data integration or data fusion between passive and active remote sensing, between spaceborne and airborne remote sensing, and between from-above and ground-based remote sensing holds promise to increase FSD detection precision and accuracy (e.g., Hakkenberg et al., 2023) as well as addressing issues of scale. Cross-platform comparisons of measurements across sensors, platforms, and scale are needed.

Repeat, high-resolution estimates of canopy structure enabled by remote sensing methods such as lidar and radar could transform our understanding of forest canopy dynamics, building off multiple decades of research enabled by long-term forest monitoring plots. Measurements of forest dynamics that have been made from traditional methods (e.g., forest inventories) have enabled insight into tree diameter growth, mortality, and gap disturbances, and how those dynamics are changing with climate change (Van Mantgem et al., 2009). However, scaling inferences from tree diameters to canopies requires simplifying assumptions about tree allometry and 3D space-filling of forest canopies, which may introduce error (Bohlman & Pacala, 2011; Farrior et al., 2016). Novel and creative means will be necessary to fuse these approaches. ITD methods, whereby algorithms are used with remote sensing data to identify individual trees via crown segmentation, may fill a crucial gap here, linking point measurements on the ground with specific individuals identified from remote sensing data taken above the canopy (Silva et al., 2022). New measurements of canopy structure from airborne and terrestrial lidar, collected systematically at the same site over comparable time frames to tree lifespans, are needed to understand the dynamics of forest structure and biomass, and how they are responding to global change. Presently, airborne lidar datasets exist for many sites from single overflights. However, many of these datasets lack repeat measurements, and when repeat measurements exist, they rarely span more than a decade (e.g., Dalagnol et al., 2021; Kellner & Asner, 2014). Repeat measurements taken over multiple decades will enable understanding of competitive interactions within forest ecosystems, and how forest structure and composition are changing in response to global and local influences in climate, nutrient availability, and land use.

The theoretical limitations facing FSD measurement are nontrivial and have practical ramifications. To our knowledge, no comprehensive list of all FSD measurements has been published to date. While this effort would be arduous and time-consuming given the range of sensors and algorithms employed and the pace at which advancement occurs, such a list would be a valuable tool to guide future research as well as aid the standardization of FSD derivation. Lacking a thorough inventory of the landscape of FSD measurement, creating consensus and standards is difficult. Currently, there are disjunct reports on various approaches to FSD measurement focused on specific subfields, thus hindering applications of FSD in future research. There is also no consensus about the spatial scale or grain size at which many FSD measurements should be taken, nor is there a robust statistical treatment or analysis of the role of scale (Garabedian et al., 2014). FSD metrics are often calculated at the scale of interest of a given function (Beland et al., 2019) without explicit regard given to the stability or scale-dependency of those FSD metrics (Atkins et al., 2023). There is a clear need to understand how spatial grain and extent factor into FSD measurement. FSD measurements that capture spatial and temporal change in forest structure are needed to track changes in structural diversity equivalent to alpha, beta, and gamma diversity (Fotis, Morin, et al., 2018; Fotis, Murphy, et al., 2018; Latifi & Valbuena, 2019). It is also necessary to invest efforts in the identification, classification, and detection of attributes of structural diversity that are rare, uncommon, or critically important, but difficult to measure as well as the development of indices that are sensitive to changes of such rare structural features.

Advances in FSD theory will also catalyze work to characterize broad structural patterns across biomes (Atkins et al., 2022; Ehbrecht et al., 2021; Fahey et al., 2019; Hakkenberg & Goetz, 2021), codify FSD metric derivation (Walter et al., 2021), and incorporate theory from disparate fields into FSD measurement (Shiklomanov et al., 2019; Verbeeck et al., 2019). Integrating FSD measurement with existing field survey data and in situ sensor networks has a huge potential to advance research, as does integration with mechanistic modeling approaches (e.g., use of FSD measurements to test structural assumptions of ecosystem models and/or to create more parsimonious models using integrative FSD metrics). Measurements of forest dynamics made from forest inventory data have provided insight into tree diameter growth, mortality, and gap disturbances, and how those dynamics are changing with climate change (Van Mantgem et al., 2009). However, scaling inferences from individuals to canopies requires simplifying assumptions about tree allometry and 3D space-filling of forest canopies (Farrior et al., 2016; Fisher et al., 2018), which may introduce error. Additionally, many remote sensing data products can be fused to create more robust measures of FSD, yet more work is needed to refine algorithms (Silva et al., 2021). Data fusion of such heterogeneous data streams may alleviate these issues but may require further advances in modeling, information-theoretic approaches, and cyber infrastructure. Composite metrics or indices could be created by combining disparate data, providing further understanding of the natural world. While technological and theoretical advances will move FSD measurement forward in the coming decade, there are current needs and opportunities within and across disciplines that can be addressed in the near term (Valbuena et al., 2020).

One key issue is the limitations that exist in the ability to access, process, and use FSD data. Development of global, national, and regional spatial data infrastructure initiatives aims to improve sustainable natural resource and environmental management by optimizing cross-national, multiagency partnerships. Infrastructure initiatives should fundamentally focus on facilitation and coordination of spatial data exchange among stakeholders from different jurisdictions and applied fields, fostering partnerships among governmental agencies, intergovernmental partnerships, nonprofit environmental organizations, commercial sector, and academic and research institutes (Rajabifard & Williamson, 2001). The NEON, NASA, OpenTopography, and the USGS 3D Elevation Program are examples of free resources for remote sensing data that range from site-level to global data coverage. We must also consider the necessity of increased abundance of and access to training and education resources to work with FSD data and tools. Open-source platforms that can be used to process and quantify FSD data do exist (e.g., QGIS, Fusion, Google Earth Engine, Python, R, CloudCompare). While educational resources providing free tutorials and webinars (e.g., NEONscience.org, earthdatascience.org, earthdata.nasa.gov, Data Carpentry) for accessing and working with FSD data also exist, allocation of greater financial resources to support these efforts is needed. The future of FSD measurement lies at the nexus of people and technology. The ability to work with these data must not be limited by privilege or access (Dwivedi et al., 2022).

CONCLUSIONS

Advances in technology, data distribution, and theory have driven the evolution of FSD measurement; however, further work is needed to realize its full potential. Grounding FSD measurement in theory and creating standardized approaches will expand our ability to understand forest and ecosystem dynamics and make cross-scale and -system comparisons. We face an abundance of data coupled with the need to develop rigorous methods and theories to work with that data. We also must empower and enable the community to work with these data. While there is much work to do, thoughtful consideration of how FSD can be used to broaden the scope of ecological research may be transformative for all branches of ecological and environmental research.

ACKNOWLEDGMENTS

This manuscript was conceived at a National Science Foundation (NSF)-funded workshop, “Exploring New

Dimensions of Forest Ecosystems with Structural Diversity." NSF award number 1924942 was granted to Principal Investigators/Co-Authors Drs. Elizabeth A. LaRue and Brady S. Hardiman and PI Dr. Songlin Fei.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Datasets utilized for demonstration purposes are available in: Shimada et al. (2014) (https://doi.org/10.1016/j.rse.2014.04.014), Atkins et al. (2021) (https://doi.org/10.5194/essd-13-943-2021), NEON (2022a, 2022b) (https://doi.org/10.48443/73zn-k414, https://doi.org/10.48443/ymmp-fr93), and NEON (2023) (https://doi.org/10.48443/ehnm-xd88).

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How to cite this article: Atkins, Jeff W., Parth Bhatt, Luis Carrasco, Emily Francis, James E. Garabedian, Christopher R. Hakkenberg, Brady S. Hardiman, et al. 2023. “Integrating Forest Structural Diversity Measurement into Ecological Research.” *Ecosphere* 14(9): e4633. https://doi.org/10.1002/ecs2.4633