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Opinion

Standardizing Ecosystem Morphological Traits from 3D Information Sources

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3D-imaging technologies provide measurements of terrestrial and aquatic ecosystems' structure, key for biodiversity studies. However, the practical use of these observations globally faces practical challenges. First, available 3D data are geographically biased, with significant gaps in the tropics. Second, no data source provides, by itself, global coverage at a suitable temporal recurrence. Thus, global monitoring initiatives, such as assessment of essential biodiversity variables (EBVs), will necessarily have to involve the combination of disparate data sets. We propose a standardized framework of ecosystem morphological traits – height, cover, and structural complexity – that could enable monitoring of globally consistent EBVs at regional scales, by flexibly integrating different information sources – satellites, aircrafts, drones, or ground data – allowing global biodiversity targets relating to ecosystem structure to be monitored and regularly reported.

Highlights

3D-imaging data acquired from a variety of platforms have become critical for ecological and environmental management. However, the use of disparate information sources to produce comprehensive and standardized global products is hindered by a lack of harmonization and terminology around ecosystem structure.

We propose a sensor- and platform-independent framework which effectively distils the wealth of 3D information into concise ecosystem morphological traits – height, cover, and structural complexity – easy to conceptualize by ecologists and conservation stakeholders lacking remote sensing background.

The conceptual disaggregation of ecosystem structure would contribute to defining and monitoring essential biodiversity variables obtained from 3D imaging that can be used to inform progress towards the UN 2030 Sustainable Development Goals and other international policy targets.

The Challenge of Monitoring Biodiversity Goals Globally

Remote sensing (RS) (see Glossary) technologies provide excellent resources to support spatially explicit monitoring of biodiversity change, in a globally consistent and repeatable fashion [1–4]. To date, international, national, and regional monitoring of biodiversity is conducted through the assessment of indicators that are driven by a heterogeneous set of primary observations [5]. **Essential biodiversity variables (EBVs)** are designed to harmonize key aspects of biodiversity, from genes to landscape, to produce a comprehensive yet concise set of standardized observations that indicate how key aspects of biodiversity are changing [6–8]. RS technologies have the capacity to inform a variety of EBVs, and there are a number of informative reviews developing and proposing relevant data sets and image acquisition programs (e.g., [9–11]). One area where recent advances in RS have seen tremendous growth is the detection and monitoring of the 3D structure of ecosystems, through **3D-imaging** technologies such as **light detection and ranging (LIDAR)**, **synthetic aperture radar (SAR)**, or **digital aerial photogrammetry (DAP)**. These technologies have contributed to the spatial quantification of biodiversity assets, particularly in relation to species, community, and ecosystem structure [12–17]. However, most studies have utilized 3D-imaging collection, processing, and analysis approaches that are not generalizable beyond the location and study concerned. This limits their ability to provide global solutions for assessment of EBVs that relate to ecosystem structure [6,18].

In this contribution, we propose a standardized framework to enable practical evaluation of ecosystem structure EBVs by consolidating disparate 3D-imaging data sources into a common workflow for deriving ecosystem morphological traits. Considering the practical limitations associated with these 3D-imaging technologies from spaceborne or airborne

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platforms (Box 1), we propose the characteristics of a standardized framework for practical application of 3D-imaging data sources and identify a shortlist of EBVs that can be retrieved from these. We then convey pathways for assessing EBVs both nationally and globally, advocating for a system that makes the most of all locally available data while maintaining global consistency in the primary observations evaluated for assessing EBVs [6,7].

Practical Limitations to Using RS 3D-Imaging Data to Inform Global Efforts

Global coverage of an ecosystem structure EBV cannot be achieved using a single 3D-imaging sensor/platform combination. While SAR data are available globally from a number of satellite providers, both current and planned satellite-based LIDAR observations present several limitations for the monitoring of biodiversity (see Table I in Box 1). This is because they are sample based [2,19] and thus unable to measure EBVs requiring spatially continuous data sets, such as habitat fragmentation. While Skidmore *et al.* [10] assessed the potential of RS-informed EBVs using spaceborne sensors only, we argue that the addition of airborne LIDAR data [also called **airborne laser scanning (ALS)**], whenever available, can improve the robustness of EBV estimates [20]. In fact, many EBVs are compromised by geographical bias in the availability of species richness or other data related to biodiversity [21]. The incorporation of airborne data acquisition in EBV derivation faces the same biases, with most national ALS programs occurring in Europe, North America, and Australia, but significant gaps in tropical forests or drier regions, particularly in Africa, south and central Asia, and South America (see Table II in Box 1). Over time, more countries will incorporate ALS surveying into national programs as the availability of the technology increases and costs decrease. Moreover, the advent of even finer-scale 3D-imaging data from, for example, remotely piloted platforms utilizing lightweight LIDAR or stereoscopic restitution of optical images [22,23] allows EBVs to be retrieved over hotspot areas and later extrapolated to larger areas using additional RS sources whenever full LIDAR coverage is lacking [1]. Multiplatform and multisensor systems, with clear definitions of the aspects of ecosystem structure encompassed, provide the only realistic solution for global assessments of EBVs that are practical, economically viable, and sustainable in time [8,24].

Another challenge that hinders the use of these 3D data sources in conservation is the high degree of specialization required for their basic processing. To date, open data specifications often provide a limited set of processed products, such as terrain or canopy models, which are more manageable but less relevant to ecology and conservation. Thus, there is a need for distilling out the complexity of 3D-imaging information into concise ecosystem morphological traits that are easy to conceptualize and quantify [7,25,26] (see Figure I in Box 1). Making the retrieval of these traits easily available [27] would foster the uptake of these data sets by nonspecialized stakeholders locally, and also globally by assuring compliance with protocols for involving metadata and the uncertainty of primary observation in EBV reporting [6,7], following open science principles [28].

A Standardized Framework of EBVs of Ecosystem Structure That Accommodates any Type of 3D-Imaging RS Data

Different aspects of ecosystem structure EBVs may be informed directly from 3D-imaging data, with or without calibration with ground data (Table 1). The definition of the underlying terrain is critical, which can only be detected using LIDAR or SAR. By quantifying the elevation of the ground terrain, information on the height and arrangement of structural elements above the terrain surface can be obtained. Once measured, changes in the height or cover of all of the ecosystem **structural elements** over space and time then inform EBVs on ecosystem

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extent, connectivity, and fragmentation [5,29–31] (Table 1). This vertical structure is typically assessed using statistics describing characteristics of either the returning waveform of a LIDAR pulse, backscatter of a SAR response, or morphological patterns from optical image matching. These include intensity of the backscatter, and variability, skewness, or proportions of returns along vertical strata, etc. [14,23,32–38] (Table 1). In turn, these metrics provide descriptors of **ecosystem height**, **ecosystem cover**, and **ecosystem structural complexity** [26,39], which can inform EBVs related to ecosystem traits such as canopy height, plant area index, and foliage height diversity [13], or coral reef elevation, cover, and rugosity [16]. These characteristics describe complementary aspects of ecosystem structure [26], with mechanistic relationships to properties such as biomass [40] or leaf area index (LAI) [34], and thus there is a wide consensus in the literature on using them [13,14,16,17,25,39]. When clustered spatially, comparable assessment across wide spatiotemporal spans, such as mapping habitat structure across scales, can be achieved [29,36,41].

These three components of ecosystem structure constitute the backbone of a standardized framework of a few concise and complementary ecosystem morphological traits that can be derived from any available data (Figure 1). The proposed framework is applicable and relevant to any terrestrial or marine environment [16]. We recognize these as descriptors of an ecological community as a whole, not individual organisms (structural elements), and as such they are to be evaluated for a given area. Specifically, area-based estimation at a spatial resolution of 15–25 m would ensure a sample representative to the community [26,33,35,36,39,41], and would be commensurate with the footprint of satellite LIDAR and free and open optical data sets such as Landsat and Copernicus Sentinel (Box 1). Given the variety of sensors and platforms that can contribute data to these components of structure, uncertainty in the measurement should be assessed and accounted for in the final product [6,29]. These should be included into an ecosystem structure 'data cube' along with metadata on data sources, methods, and dates, all critical to enable change detection [8]. As the GEDI (Global Ecosystem Dynamics Investigation) mission is completing the first comprehensive global LIDAR dataset [2] (Box 1), the processing workflows for measuring ecosystem morphological traits and the determination of their uncertainties from GEDI should set a precedent on how the ecosystem structure components are to be derived from other 3D-imaging tools. As an example, tools like rGEDI [27] can provide new opportunities to allow practitioners from local to global scales to make use of GEDI data in compliance with the EBV framework. To seek harmonization and global consensus, subsequent workflows for retrieval of ecosystem morphological traits from other sources like airborne LIDAR [19] or SAR [42] should seek to emulate the exact parameters established after the first use of GEDI in the EBV data portal [8]. Future research on physically based radiative transfer models (such as Hancock *et al.* [19]), especially once they become spectrum invariant and thus valid from light to radar, will be the most reliable pathway for homogenizing the retrieval of EBVs from different sensors and missions [43].

From Standardized Components of Ecosystem Structure Locally to EBVs Globally

Coupled with field data for calibration, these three components of ecosystem structure – height, cover, and structural complexity – can also be employed as a proxy to estimate many other ecosystem characteristics relevant to EBVs [44,45] (Table 1, Figure 1). These include, for instance, LAI or carbon stocks, which are variables typically predicted using LIDAR data calibrated with ground observations [20,40,46–49]. Methods coupling LIDAR data with ancillary information may also inform additional EBVs beyond ecosystem extent and structure. Examples are ecosystem functional diversity [13] or community composition [15,33,34]. They can also support quantitative assessments of species abundances and distributions [12,50–53], and are useful in the

Glossary

3D imaging: also known as 3D RS, the concept includes any RS method that detects 3D positions of ecosystem structural elements. LIDAR, SAR, and digital photogrammetry are specific types of 3D-imaging data sources.

Airborne laser scanning (ALS): airborne LIDAR systems fire discrete pulses of green and infrared light from the height of a flying aircraft, so that the beam widens to about 0.3–0.5 m in diameter upon reaching the surface. When targeted on vegetation, only a portion of the laser pulse is backscattered from the upper crowns, while other components return off leaves and branches further down the canopy, understory vegetation, and the ground (see Figure I in Box 1). Thus, multiple returns backscattered off the different elements of the targeted ecosystem are obtained from a single pulse, resulting in an informative 3D point cloud of scanned LIDAR returns.

Digital aerial photogrammetry (DAP): 3D information from stereoscopic restitution of two or more images acquired from an aerial platform. While digital photogrammetry can be obtained from a variety of platforms (close range on the ground, or airborne/satellite imagery), the recent spread use of drones has popularized structure-from-motion methods which deliver dense DAP data.

Ecosystem cover: percentage of a fixed area covered by the vertical projection of the ecosystem structural elements. Common terms employed for vegetation are plant area index [13,34], or colony cover for corals [16].

Ecosystem height: average height of the highest ecosystem structural elements. Common terms employed are top of canopy height in forests [40] or reef elevation for corals [25].

Ecosystem structural complexity: variability in height and/or cover of the ecosystem structural elements. Standard deviation and coefficient of variation are common measures of ecosystem complexity [25,35,39]. Rugosity is a common term employed for both forest canopies and benthic habitats [53].

Essential Biodiversity Variables (EBV): Measurements required to report the status and monitor trends in biodiversity change globally, to inform decision makers in management and policy [7,24].

estimation of many ecosystem services [54]. These morphological traits are focused on an ecosystem perspective, with mechanistic relationships to properties like LAI or biomass [13,14,40], which makes them suitable to feed in models that can derive reliable EBVs, such as the Ecosystem Demography or Dynamic Global Vegetation Models and other process-based models [11]. Moreover, the parameterization of vegetation structure-species richness models, using data from field-based sampling of species abundances or presence/absence data-allows for the generation of spatially continuous predictive maps [8,17,45,50,51,55]. Table 1 details the range of ecosystem attributes that can be reliably estimated using 3D-imaging methods and the subsequent EBVs that they can inform.

Given the simplicity and ecosystem-focused conceptual basis of these components, the specific RS platform or technology to deliver their mapping can vary across space and time (Table 1), even allowing future adoption of hitherto unknown technologies. For global assessments of ecosystem structure EBVs, the most advantageous approach for EBV retrieval is to couple available LIDAR data with other RS sources. Figure 1 illustrates the variety of data fusion pathways that may be employed according to data availability in any area. Since no single data combination will attain the whole globe at suitable temporal recurrence, the framework on Figure 1 seeks to make the different pathways compatible, so that many of them may be approached towards a same goal. Common to many approaches is the use of existing, free and open, satellite missions to extrapolate LIDAR estimates beyond the acquisition area. These include optical imagery such as Landsat or Sentinel [1,4,56], or data from SAR missions [3,42] (see Table I in Box 1). There is a growing consensus in considering that LIDAR can obtain direct measurements of these ecosystem traits [13,29,35,39], whereas the current state-of-the-art for other RS sources such as SAR is that they derive variables that can be used as proxies for estimation and upscaling [4,42,43,56] (Figure 1). In particular, SAR is well suited to provide good proxies for ecosystem height [3,42], whereas ecosystem cover is best retrieved from spectral imagery [1,4]. The resulting spatially continuous maps derived from 3D imaging allow generation of large-area inventories for guiding biodiversity monitoring and conservation assessments [12]. These have significant potential for reporting key indicators to inform both regional and global policy targets [24], such as UN 2030 Sustainable Development Goals (SDG), post-2020 Global Biodiversity Framework, and UN Decade of Ecosystem Restoration. For example, these morphological traits could be used to assess ecosystem restoration efforts [57] (Aichi Target 14 and 15 of the Convention on Biological Diversity), sustainable ecosystem management [58] (SDG Target 15.2 and Aichi Target 5), and contribution of biodiversity towards enhancing forest carbon stocks [12,30] (Aichi Target 15).

Compliance of This Framework with the EBV Definition

The relevance of the framework providing three basic components of ecosystem structure as primary observations informing EBVs is contingent on them being feasible to reproduce (robustness), sensitive to change, and globally consistent [7]. The EBVs ought to be retrieved independently from the sensor and platforms employed for measuring them. The consistency of 3D-imaging in delivering these components of ecosystem structure has been conclusively demonstrated across biomes and ecosystem types [3,4,16,26,29,41] (Table 2). Vegetation height strongly correlates with forest carbon sequestration [40]. Vegetation cover has been used to map tropical forest canopy gaps and light environment [14,22,59], as well as local diversity of forest plants, fungi, lichens, and bryophytes [51]. Vegetation height, cover, and structural complexity have been used to classify native species distribution in tropical savannahs and grasslands [34,46,60] and reveal fine-scale linkages between microstructure and photosynthetic functioning in tundra ecosystems [61]. These three

Light detection and ranging (LIDAR): LIDAR systems scan targeted surfaces by emitting laser pulses and detecting their reflection. Ground-based platforms are used to get an informative 3D cloud of scanned LIDAR returns over individual samples or transects. Airborne platforms obtain similar information over continuous swaths of land, with a trade-off between the density of 3D information and its coverage: drones obtain denser data over limited extents and aircrafts acquire sparser data covering whole regions. LIDAR pulses emitted from satellites cover an entire plant community, thus delivering a whole waveform instead (see Figure I in Box 1). Nonetheless, the information can be similarly utilized and the main difference is that satellite LIDAR provides global coverages but only at discrete samples (i.e., not spatially continuous).

Remote sensing (RS): Methods acquiring information from ecosystems at a distance. RS may involve a variety of sensors (e.g., spectral cameras, lasers, radar) on a variety of platforms: ground-based, drones, airborne or spaceborne. The type of data collected depends on the sensor/platform combination, 3D-imaging is one specific type of RS in which the output information is 3D positions of objects.

Structural elements: sessile biological entities constituting the biophysical environment of an ecosystem (e.g., plants or corals).

Synthetic aperture radar (SAR): an extremely large antenna would be needed in order to detect objects through very long distances using radar wavelengths. To avoid this, SAR simulates a long aperture through the flight path of a moving side-looking platform, airborne or spaceborne. The outcome products provide 3D structure information of the targets, at 1–5-m spatial resolutions. SAR can penetrate clouds, which makes it a useful technique in rainforests and mountainous regions. Depending on the wavelength (e.g., C-band or L-band) different ecological features can be recognized.

components of ecosystem structure can also be applied to marine habitats [25] as habitat indicators for marine life [53]. As a result, the framework supports the inherent requirement of EBVs to be 'ecosystem-agnostic' state variables, allowing generalizable relationships across biomes [6,62] (Table 2).

Several studies have demonstrated the ability of structural components to be sensitive to change. Authors have applied multitemporal LIDAR data for mapping and monitoring forest changes in tropical (e.g., [63]), temperate (e.g., [64]), and boreal (e.g., [47]) forest ecosystems (Table 2). The utility of multitemporal LIDAR for carbon dynamics monitoring

Box 1. 3D-Imaging Data Sources: Current Availability and Feasibility for Assessing EBVs

Both satellite and airborne sources of 3D imaging have capabilities for deriving similar information relevant to our ecosystem structural framework (Figure I) [19]. Each of them, however, also has its own practical limitations for long-term monitoring of EBVs.

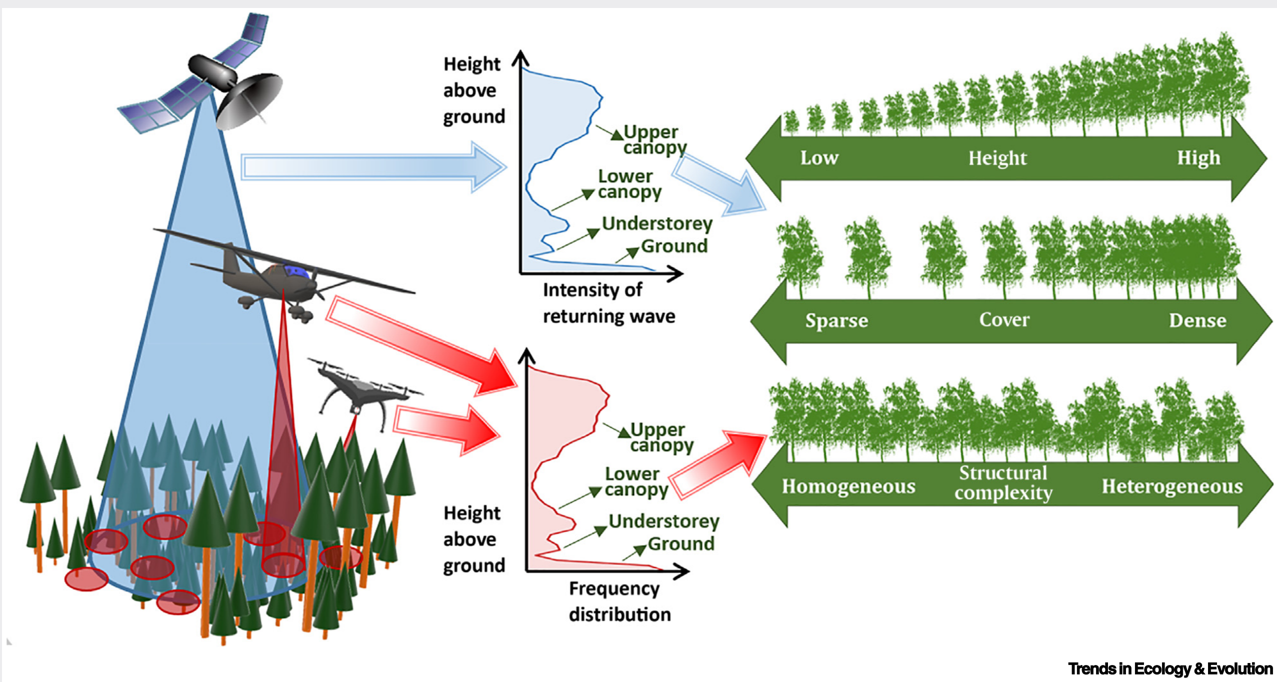

Figure I. Basic Common Procedures for Deriving Morphological Traits from Different 3D-Remote Sensing (RS) Data Sources. Satellite light detection and ranging (LIDAR) provides discretely spaced pulses with a large footprint, whereas airborne laser scanning (ALS) or drones take a continuous scan throughout the surveyed area. While they produce different raw data, the procedures to derive ecosystem morphological traits are similar for all, satellite or airborne 3D-imaging.

Spaceborne Platforms

There are two civilian spaceborne LIDAR sensors currently operational – NASA's ICESat-2 and GEDI [4] – which provide potential opportunities for deriving EBVs informed by LIDAR from space (Table I). These satellites have restricted operations though – 3 years for ICESat-2 and 2 for GEDI – which limits their utility for long-term monitoring of EBVs. Neither mission is designed to acquire laser pulses over the same location twice, and thus they are not designed to detect information on change, which is a key characteristic of any EBV [7]. While ICESat-2 is global, GEDI is limited to the orbit of the International Space Station (latitude limitation at 51.6° N and S). Satellite LIDAR systems obtain discrete pulses sampling a footprint of diameter 17–25 m on the ground (Figure I), which are separated by distances of around 0.6–2.5 km along track and 0.6–3.3 km across track, making it difficult to assess ecosystem traits involving neighboring analyses, such as ecosystem extent and fragmentation (Table 1). GEDI data sets [2] and tools for easy derivation of ecosystem traits from them [27] are readily available. Overall, the greatest potential of satellite LIDAR for global EBV assessments is in combination with optical sensors [4], or with SAR [42] (Figure 1), with many relevant missions coming up in the next years (Table I). There are numerous synergies between missions, such as the possibility of using SRTM data to define the terrain elevation, whenever higher-resolution topographic information is unavailable [58].

Table I. Satellite Missions That May Be Used to Support Ecosystem Structure Assessments (Figure 1) towards the UN Agenda's 2030 Sustainable Development Goals[a]

Sensor	Satellite/program	Agency	Starting from year	Link
LIDAR	Global Ecosystem Dynamics Investigation (GEDI)	NASA	2018	https://science.nasa.gov/
	Ice, Cloud, and land Elevation Satellite-2 (ICESat-2)	NASA	2018	https://icesat-2.gsfc.nasa.gov/
Optical	Earth Observing System [Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), etc.]	NASA	1972	https://eospso.nasa.gov/
	Copernicus Global Monitoring (Sentinel)	ESA	2014	http://www.copernicus.eu/
	High-Definition Earth Observation Sat. (HDEOS)	CNSA	2015	https://directory.eoportal.org/
SAR	BIOMASS	ESA	2021	https://earth.esa.int/
	Phased Array type L-band SAR (PALSAR)	JAXA	2006	https://www.eorc.jaxa.jp/
	NASA-ISRO Synthetic Aperture Radar (NISAR)	NASA–ISRO	2022	https://nisar.jpl.nasa.gov/
	TanDEM-X	DLR	2014	https://tandemx-science.dlr.de/
	TanDEM-L	DLR	2022	http://www.dlr.de/
	Shuttle Radar Topography Mission (SRTM)	International	2000	https://www2.jpl.nasa.gov/

[a]Abbreviations: CNSA, China National Space Administration; DLR, German Aerospace Center; ESA, European Space Agency; ISRO, Indian Space Research Organization; JAXA, Japan Aerospace Exploration Agency; NASA, US National Aeronautics and Space Administration.

Airborne Laser Scanning (ALS)

Several national/regional surveying programs are producing ALS data sets covering entire countries (Table II), many of them with revisited coverages. These low-density data sets (typically 0.5–2 pulses·m^2) are demonstrably useful for ecosystem characterization and ecological applications [29,35,39]. There is general consensus on methodologies employed to derive ecosystem morphological traits from these data sets [15,16,26], and they are increasingly becoming publicly available along with free tools for data processing (see opentopography.org). These open up unique opportunities for generating habitat traits and classifications that can be consistently obtained throughout entire regions or countries. Using GEDI as a standard [2], the derivation of those same morphological traits from airborne LIDAR (Figure I) should follow Hancock *et al.*'s [19] processing steps to facilitate the homogenization of disparate airborne acquisition settings.

Table II. Examples of Publicly Available Airborne ALS Data Sets from National/Regional Surveying Programs

Country/state	Agency/program	Link
Canada	Agriculture and Agri-Food Canada	http://open.canada.ca/
Australia	GeoScience Australia and Terrestrial Environment Research Network	https://www.tern.org.au/
Denmark	Kortforsyningen	http://download.kortforsyningen.dk/
Finland	Maanmittauslaitos/National Land Survey of Finland (NLSF)	http://www.maanmittauslaitos.fi/
Germany/North Rhine-Westphalia (NRW)	OpenNRW	https://open.nrw/
Netherlands	Actueel Hoogtebestand Nederland (AHN)	http://lists.osgeo.org/
Spain	Instituto Geográfico Nacional (IGN)/Plan Nacional de Ortofotografía Aérea (PNOA)	http://centrodedescargas.cnig.es/
UK	UK Environment Agency	https://data.gov.uk/
USA	US Geological Survey (USGS)/US Department of Interior	https://catalog.data.gov/

has been shown in subtropical [48] and conifer forests [47]. Temporal changes in LIDAR-derived EBVs are important for assessing ecosystem dynamics, including tree growth, biomass dynamics, and carbon flux. Almeida *et al.* [14] provides an example of how evolving methodological developments over decades can be standardized into simple measures, allowing long-term monitoring. Thus, despite the technological changes constantly occurring over decades, consensus over the derivation of these morphological traits of ecosystems from 3D-imaging technologies can bring about the consistency needed for long-term monitoring.

Concluding Remarks and Future Perspectives

We provide a rationale that ecosystem structure can be concisely defined by three key components: ecosystem height, cover, and structural complexity. This conceptual disaggregation simplifies the wealth of information provided by 3D-imaging data sources, allowing ecosystem structure information obtained from any sensor, platform, or scale, including ground information (such as field-based LAI), or future satellite missions and technological developments, to be combined effectively towards long-term global goals. These morphological traits are focused on describing the ecosystems, not tailored to the available methods to retrieve them, which is key to the determination of EBVs.

This framework is mandatory to monitor global targets over decades, as no seamless global retrieval of an EBV focused on ecosystem structure is attainable using a single 3D-imaging data source. We challenge the widespread notion that airborne 3D-imaging has no role to play in global EBV retrievals, and our framework aims to educate users on the potential role these data can play. We wish to encourage national programs acquiring 3D-imaging data (see Table II in Box 1) to consider routine delivery of these three easy-to-conceptualize ecosystem components. Such morphological traits presented as gridded products would foster uptake of these expensive data sets

Outstanding Questions

Robustness must be secured by researching on the reproducibility of GEDI workflows with other 3D-imaging sensors, through the derivation of physically based spectrum-invariant radiative transfer models.

Sensitivity to change will differ from one RS-derived product to another, and levels of uncertainty in the measurement of each morphological trait also differ. How can such differences be accommodated within the framework to allow for unbiased long-term monitoring of change with clearly stated degrees of uncertainty?

Global consistency needs to be further supported by research on

Table 1. Summary of Ecosystem Characteristics Relevant to EBVs That Can Be Derived from 3D-Imaging Sources, with Example References for Different Pathways for Their Retrieval [65][a]

EBV class / subclass	Ecosystem characteristic	Requirements for assessing nationally							Requirements for assessing globally							Suitable products or estimated variables
		ALS	DAP	SatL	SAR	MS	Field	Other	ALS	DAP	SatL	SAR	MS	Field	Other	
Ecosystem structure / Habitat structure and condition	Height	[37]	[36]	[30]	[56]	[54]	[12]	[35]	[43]		[16]	[16]				Top or average height above ground.
	Density / Cover	[34]			[56]	[54]					[4]		[4]			Proportion of heights above thresholds. Estimates of LAI or gap fraction using ground data for calibration.
	Complexity	[33]	[50]			[64]		G3D [21]	[23]	[14]	[16]	[16]			G3D	Variability or entropy of lidar heights (rugosity), or leaf area density profiles. Estimates of biomass distribution using ground data for calibration.
Ecosystem structure / Ecosystem extent and fragmentation	Habitat area	[37]						[35]					[1]			Area under certain characteristics, e.g. vegetation cover above threshold
	Habitat connectivity and fragmentation	[29]														Combination: vegetation height, density and vertical structure
Ecosystem Function	Carbon sequestration	[43]		[41]	[56]			G3D [45]	[17]		[17]			[17]	[2]	Estimates of above (or below) ground biomass using ground data for calibration
	Decomposition	[65]	[56]		[56]											Estimates of coarse woody debris using ground data for calibration
	Disturbance regime	[66]				[64]										Area affected by disturbances
Ecosystem composition / Taxonomic diversity	Species diversity / Richness	[31]						HS [11]	[13]			[3]	[39]		HS [13]	Estimates of alpha / beta diversity and richness using presence/absence data for calibration
Species populations	Species distributions	[49]					[53]	[35]	[48]					[25]		Estimates of habitat suitability for species using presence/absence data for calibration
	Population abundance / Ecosystem classes	[27]														Combinations of vegetation height, cover and complexity. Estimates of ecosystem classes using ground data for calibration
	Population structure by size class	[53]						G3D [59]	[38]						G3D	Combination of estimates of biomass and species distribution using ground data for calibration.

Note:

	Required		Useful but not required
	Required in combination		Not required

[a] Abbreviations: DAP, digital aerial photogrammetry; Field, field data acquired on the ground; G3D, ground-based 3D imaging (e.g., terrestrial LIDAR or proximal photogrammetry); HS, hyperspectral; MS, satellite multispectral; SatL, satellite LIDAR.

by conservationists, enhancing their global and national applicability in biodiversity policy and practice. We advocate for an EBV retrieval system which is sufficiently flexible to allow the generation of globally consistent information from a variety of methods and sensor combinations, making efficient use of LIDAR data available locally. Such a system would make a vital contribution towards future biodiversity goals and the prioritization of conservation actions.

In order to encourage widespread adoption, further research is needed on further ensuring robustness, sensitivity, and global consistency in the retrieval of EBVs from 3D-imaging data (see Outstanding Questions). Robustness is to be achieved by securing reproducibility in the application across different sensors/platform combinations. Sensitivity to change is an important characteristic of EBVs, and with rapid technological advances, research should focus on ensuring the comparability of data sets acquired in the past, present, and future. Global consistency in the measures of ecosystem structure can be achieved by using GEDI as the standard to follow. The current trend is in considering that LIDAR can measure at least some of these ecosystem morphological traits directly, and even better than field methods, which brings about a change of paradigm since now LIDAR can become the ground truth to compare against other methods. Quantification of uncertainties in measuring these morphological traits from each possible 3D-imaging method allows for their optimized combination and multitemporal comparison. Important research avenues lie in demonstrating relationships of each of these ecosystem structure components with biodiversity assets, noting that these will differ among biomes. We consider that this framework may facilitate just that, enabling the use of 3D-imaging technologies to identify hotpots for action in conservation, and greatly enhancing the use of 3D-imaging data sets by those who

the relationships of ecosystem morphological traits across different biomes and ecosystem types.

How do each of the ecosystem structure components relate to the different dimensions of biodiversity: taxonomic, phylogenetic, or functional? Which are the relevant scales for those relationships and how are they affected by coregistration errors?

How can changes in these ecosystem structure components be relevant to biodiversity conservation policy and practice? How can the global community of RS practitioners, ecologists, and biodiversity policy experts work together to further the inclusion of the proposed framework in the policy-making decision process? We encourage engaging with The Group on Earth Observation Biodiversity Observation Network (GEO BON) to overcome these challenges.

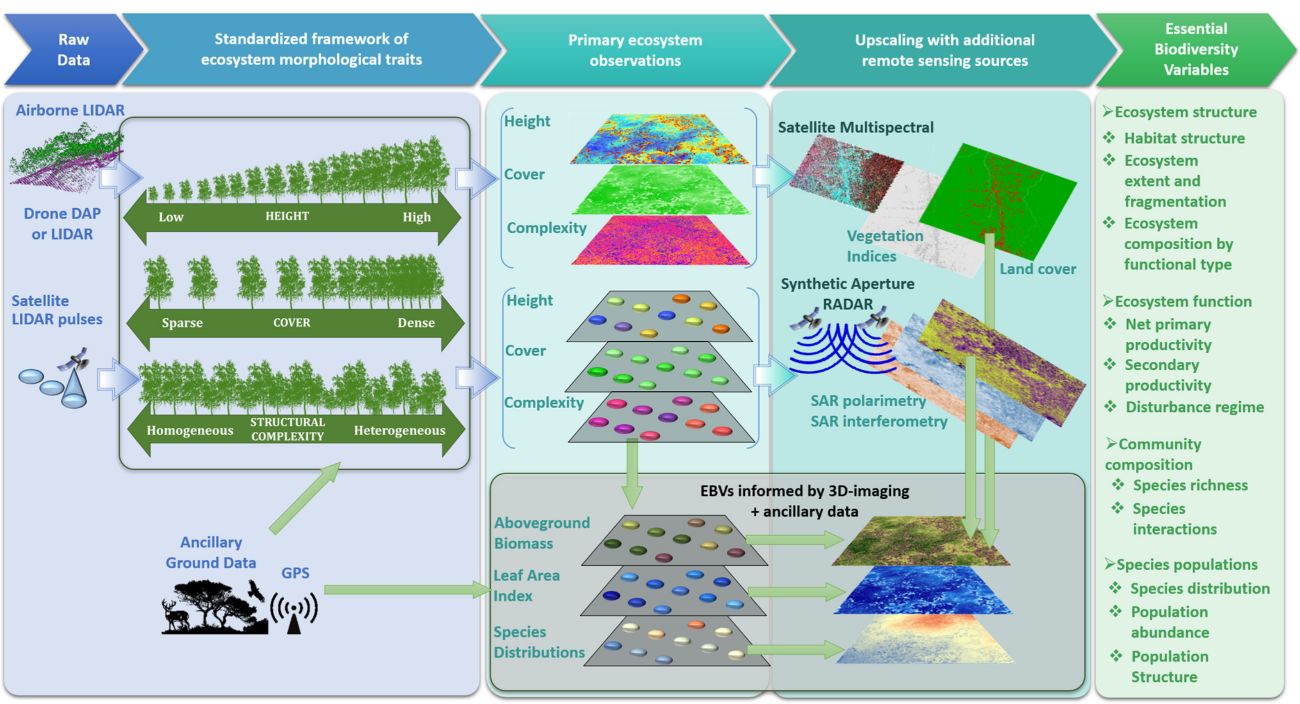

Figure 1. Schematic Diagram Showing the Practical Pathways for Deriving EBVs from Various Potential Sources, Using a Framework of Standardized Ecosystem Morphological Traits Derived from 3D-Imaging and/or Ground Information.

For a Figure360 author presentation of Figure 1, see the figure legend at https://doi.org/10.1016/j.tree.2020.03.006.

Abbreviations: DAP, digital aerial photogrammetry; EBVs, essential biodiversity variables; GPS, global positioning system; LIDAR, light detection and ranging; RADAR, radio detection and ranging; SAR, synthetic aperture radar.

Table 2. Recent 3D-RS Studies on Ecosystem Structure for Worldwide Dominant Vegetation Types and/or Involving Change Detection

Vegetation type	Refs	System	Multitemporal	Ecosystem characteristics (see Table 1)
Tropical rainforest	Almeida *et al.* [14]	Field measurements, airborne laser scanning, and ground-based LIDAR	1980–2008–2015	Changes in vegetation height, cover, structural complexity, and carbon sequestration
	Smith *et al.* [59]	Ground-based LIDAR	2010–2012–2015–2017	Changes in vegetation cover and structural complexity
	Shao *et al.* [63]	Airborne laser scanning	2008–2017	Ecosystem structural complexity
Tropical savannas	Marselis *et al.* [34]	Full-waveform airborne LIDAR and ground-based LIDAR	No	Vegetation height, cover, structural complexity, and ecosystem classes
	Ferreira *et al.* [38]	Drone-based LIDAR and photogrammetry	No	Vegetation height
	Gwenzi and Lefsky [32]	Satellite LIDAR	No	Vegetation height and cover
Mangroves	Lucas *et al.* [58]	Satellite SAR and drone-based photogrammetry	1987–2016	Changes in vegetation height, cover, and carbon sequestration
Subtropical forests	Cao *et al.* [48]	Airborne laser scanning	2007–2016	Changes in carbon sequestration
	Almeida *et al.* [23]	Field measurements and drone-based LIDAR	2004–2016	Changes in vegetation height, cover, structural complexity, and carbon sequestration
Desert vegetation	Sankey *et al.* [37]	Ground-based LIDAR	2011–2012	Vegetation height and habitat area
Mediterranean forests	Lopatin *et al.* [33]	Airborne laser scanning	No	Species richness and population abundance by size class
	Hu *et al.* [67]	Airborne laser scanning	2013–2013	Changes in population structure by size class and vegetation cover
Temperate broadleaved	Moeslund *et al.* [51]	Airborne laser scanning	No	Species richness by functional type
	Hilmers *et al.* [64]	Full-waveform airborne LIDAR	2006–2008	Changes in species abundances, richness, and composition
Temperate coniferous	McCarley *et al.* [66]	Airborne laser scanning and satellite multispectral	2009–2013	Disturbance regime in vegetation cover
Shrublands	Greaves *et al.* [49]	Ground-based LIDAR	No	Shrub biomass and leaf area index
Grasslands	Fisher *et al.* [60]	Airborne laser scanning	No	Vegetation cover and ecosystem classes
	Silva *et al.* [46]	Full-waveform airborne LIDAR and satellite LIDAR	No	Vegetation height and carbon sequestration
Montane forest	Duncanson and Dubayah [68]	Airborne laser scanning	2008–2013	Changes in vegetation height, carbon sequestration, and disturbances

Using 3D-imaging data to disentangle direct and indirect effects affecting the relationships between species distributions and ecosystem structure deserves further attention. Structure alone has some limited direct influence on species and their distributions, for example, by providing cover from predators or providing nesting or hibernating sites. The disaggregation into ecosystem structure components may enable us to analyze their separate influence on microclimates, and thus species distributions.

The biggest research gap is the marine and freshwater environments. Which tools are most appropriate for measuring morphological traits in marine ecosystems? What are their relationships to biodiversity?

Table 2. (continued)

Vegetation type	Refs	System	Multitemporal	Ecosystem characteristics (see Table 1)
	Kellner *et al.* [22]	Drone laser scanning and satellite LIDAR	No	Vegetation height and carbon sequestration
Boreal forests	Matasci *et al.* [56]	Airborne laser scanning and satellite multispectral	1984–2016	Vegetation height, density, and carbon sequestration
	Zhao *et al.* [47]	Airborne laser scanning	2002–2006–2008–2012	Changes in vegetation height and carbon sequestration
Tundra	Maguire *et al.* [61]	Terrestrial LIDAR	No	Vegetation structural complexity
Wetlands	Reddy *et al.* [69]	Airborne laser scanning	2010–2012	Carbon sequestration (soil)
Benthic habitats	Ferrari *et al.* [53]	Underwater drone photogrammetry	No	Ecosystem structural complexity, community composition, and abundance
	Duvall *et al.* [25]	Airborne topohydrographic LIDAR	No	Ecosystem structural complexity
Urban forests	Song *et al.* [70]	Airborne laser scanning	2004–2008–2010	Change in vegetation height

can use them to advance ecological research and biodiversity monitoring. We would like to encourage ecology researchers to use this standardized framework in their search for relationships between ecosystem structural traits and biodiversity assets.

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