TITLE: Standardising ecosystem morphological traits from 3D information sources

AUTHOR NAMES: Valbuena, R.[1,2,3*]; O'Connor, B.[1]; Zellweger, F.[2,4]; Simonson, W.[1]; Vihervaara, P.[5]; Maltamo, M.[6]; Silva, C.A.[7,8]; Almeida, D.R.A.[9]; Danks, F.[1]; Morsdorf, F.[10]; Chirici, G.[11]; Lucas, R.[12]; Coomes, D.A.[2]; Coops, N.C.[13].

1: UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), 219 Huntington Road, CB3 0DL Cambridge, UK

2: University of Cambridge, Department of Plant Sciences in the Conservation Research Institute, Downing Street, CB2 3EA Cambridge, UK

3: Bangor University, School of Natural Sciences, Thoday building, Bangor LL57 2UW, UK

4: Swiss Federal Research Institute WSL, Zürcherstrasse 111, 8903 Birmensdorf, Switzerland.

5: Finnish Environment Institute (SYKE). Biodiversity Centre, Latokartanonkaari 11, 00790 Helsinki, Finland.

6: University of Eastern Finland, Faculty of Forest Sciences, PO Box 111, Joensuu, Finland.

7: University of Maryland, Department of Geographical Sciences, College Park, Maryland, USA.

8: School of Forest Resources and Conservation, University of Florida, Gainesville, FL, USA.

9: University of São Paulo, "Luiz de Queiroz" College of Agriculture, (USP/ESALQ), Department of Forest Sciences, Piracicaba, SP, Brazil.

10: University of Zurich, Remote Sensing Laboratories, Winterthurerstrasse 190, CH-8057 Zurich, Switzerland.

11: Università degli Studi di Firenze, Dipartimento di Scienze e Tecnologie Agrarie, Alimentari, Ambientali e Forestali, via San Bonaventura 13, 50145 Florence, Italy.

12: Aberystwyth University, Earth Observation and Ecosystem Dynamics Research Group, Aberystwyth SY23 3DB, UK.

13: University of British Columbia, Department of Forest Resource Management, 2424 Main Mall, Vancouver V6T 1Z4, Canada.

* Corresponding author: r.valbuena@bangor.ac.uk (R. Valbuena)
https://www.bangor.ac.uk/natural-sciences/staff/ruben-valbuena/en; twitter: @rubenvalpue

KEY WORDS: Essential Biodiversity Variables (EBVs); Sustainable Development Goals (SDG); light detection and ranging (LIDAR); synthetic aperture radar (SAR); digital photogrammetry.

ABSTRACT

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. Firstly, available 3D data are geographical biased, with significant gaps in the tropics. Secondly, 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 datasets. We propose a standardised 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.

MAIN TEXT

The challenge of monitoring biodiversity goals globally

Remote sensing (RS) 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 harmonise key aspects of biodiversity, from genes to landscape, to produce a comprehensive yet concise set of standardised observations that indicate how key aspects of biodiversity are changing [6-8]. Remote Sensing technologies have the capacity to inform a variety of EBVs, and there are a number of informative reviews developing and proposing relevant datasets and image acquisition programs [e.g. 9-11]. One area where recent advances in remote sensing have seen tremendous growth is the detection and monitoring of the three dimensional 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 utilised 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 standardised 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 platforms (**Box 1**), we propose the characteristics of a standardised 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].

***** approximate position of Box 1 *****

Practical limitations to use remotely sensed 3D 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 (**Box 1, Table I**). This is because they are sample-based [2,19] and thus unable to measure EBVs requiring spatially-continuous datasets, 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 (a.k.a. **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 programmes 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 (**Box 1, Table II**). Over time, more countries will incorporate ALS surveying into national programmes 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 utilising light-weight 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]. Multi-platform and multi-sensor 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 conceptualise and quantify [7,25,26] (**Box 1, Figure I**). Making the retrieval of these traits easily available [27] would foster the uptake of these datasets by non-specialised 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 standardised framework of EBVs of ecosystem structure that accommodates any type of 3D remote sensing 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 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 like 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 standardised framework of a few concise and complementary ecosystem morphological traits that can be derived from any available data (**Fig. 1**). The proposed framework is applicable and relevant to any terrestrial or marine environment [16]. We recognise 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 datasets 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 (CRAN.R-project.org) [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. In order 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.'s [19]), especially once they become spectrum-invariant and thus valid from light to radar, will the most reliable pathway for homogenising the retrieval of EBVs from different sensors and missions [43].

***** approximate position of Figure 1 *****

From standardised 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 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 (ED) or Dynamic Global Vegetation Models (DGVMs) and other process-based models [11]. Moreover, the parameterisation of vegetation structure-species richness models, using data from field-based sampling of species abundances or presence/absence data, also 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 remote sensing 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 **Fig. 1** seeks to make the different pathways compatible, so that many of them may be approached toward 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] (**Box 1, Table I**). 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-theart 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] (**Fig. 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 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 multi-temporal 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 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 standardised 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 toward 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 programmes acquiring 3D-imaging data (**Box 1 Table II**) to consider routine delivery of these three easy-to-conceptualise ecosystem components. Such morphological traits presented as gridded products would foster uptake of these expensive datasets 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, 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 datasets acquired in the past, present and future. Global consistency in the measures of ecosystem structure can be achieved by using GEDI as 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 optimised combination and multi-temporal 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 datasets by those who can use them to advance ecological research and biodiversity monitoring. We would like to encourage ecology researchers to use this standardised framework in their search for relationships between ecosystem structural traits and biodiversity assets.

Acknowledgements

This project resulted from a collaboration with the United Nations Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) which is the biodiversity assessment and policy implementation arm of United Nations Environment Programme, the world's foremost intergovernmental environmental organization. RV and DAC acknowledge the support of an EU Horizon 2020 Marie Sklodowska-Curie Action entitled "Classification of forest structural types with lidar remote sensing applied to study tree size-density scaling theories" (LORENZLIDAR-658180) at the University of Cambridge, UK. Within the framework of LORENZLIDAR, RV completed a six-month secondment at UNEP-WCMC for assessing the feasibility of LIDAR to retrieve EBVs on ecosystem structure. This secondment was carried out in the context of GlobDiversity, a European Space Agency funded project to assess the feasibility of satellite observations to support the development EBVs on terrestrial ecosystem structure and function. FZ was funded by the Swiss National Science Foundation (project number 172198) and the Isaac Newton Trust. PV acknowledges IBC-CARBON Project funded by The Strategic Research Council (SRC) at the Academy of Finland (Grant no. 312559). DRAA was supported by the São Paulo Research Foundation (#2018/21338-3 and

#2019/14697-0). A first version of this manuscript was greatly improved after very constructive comments and encouragement from the editor and three anonymous reviewers.

REFERENCES

1. Wulder, M.A. and Coops, C.N. (2014) Satellites: Make Earth observations open access. *Nature* 513, 30-31.

2. Dubayah, R. *et al.* (2020) The Global Ecosystem Dynamics Investigation: High-resolution laser ranging of the Earth's forests and topography. *Sci. Remote Sens.* 1, 100002.

3. Bae, S. *et al.* (2019) Radar vision in the mapping of forest biodiversity from space. *Nat. Comm.* 10, 4757.

4. Tang, H. *et al.* (2019) Characterizing global forest canopy cover distribution using spaceborne lidar. *Remote Sens. Environ.* 231, 111262.

5. Vihervaara, P. *et al*. (2017) How Essential Biodiversity Variables and remote sensing can help national biodiversity monitoring. *Global Ecol. Conserv.* 10, 43-59.

6. Kissling, W.D. *et al.* (2018) Towards global data products of Essential Biodiversity Variables on species traits. *Nat. Ecol. Evol.* 2, 1531-1540.

7. Navarro, L.M. *et al.* (2017) Monitoring biodiversity change through effective global coordination. *Curr. Opin. Environ. Sust.* 29, 158-169.

8. Jetz, W. *et al.* (2019) Essential biodiversity variables for mapping and monitoring species populations. *Nat. Ecol. Evol.* 3, 539-551.

9. O'Connor, B. *et al.* (2015) Earth observation as a tool for tracking progress towards the Aichi Biodiversity Targets. *Remote Sens. Ecol. Conserv.* 1, 19-28.

10. Skidmore, A.K. *et al.* (2015) Environmental science: Agree on biodiversity metrics to track from space. *Nature* 523, 403-405.

11. Dantas de Paula M. *et al*. (2020) Combining European Earth Observation products with Dynamic Global Vegetation Models for estimating Essential Biodiversity Variables. *Int. J. Digit. Earth* 13, 262-277.

12. Simonson, W.D. *et al.* (2014) Applications of airborne lidar for the assessment of animal species diversity. *Methods Ecol. Evol.* 5, 719-729.

13. Schneider, F.D. *et al.* (2017) Mapping functional diversity from remotely sensed morphological and physiological forest traits. *Nat. Comm.* 8, 1441.

14. Almeida, D.R.A. *et al.* (2019) Persistent effects of fragmentation on tropical rainforest canopy structure after 20 yr of isolation. *Ecol. Appl.* 29, e01952.

15. Asner, G.P. *et al.* (2017) Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. *Science* 355, 385-389.

16. Calders, K. *et al.* (2019) 3D Imaging insights into forests and coral reefs. *Trends Ecol. Evol.* 35, 6-9.

17. Bakx, T.R.M. *et al*. (2019) Use and categorization of Light Detection and Ranging vegetation metrics in avian diversity and species distribution research. *Divers. Distrib.* 25, 1045-1059.

18. Beland, M. *et al*. (2019) On promoting the use of lidar systems in forest ecosystem research. *For. Ecol. Manag*. 450, 117484.

19.Hancock, S. *et al*. (2019) The GEDI Simulator: A Large-Footprint Waveform Lidar Simulator for Calibration and Validation of Spaceborne Missions. Earth and Space Sci. 6, 294-310.

20. Nelson, R. *et al.* (2017) Lidar-based estimates of aboveground biomass in the continental US and Mexico using ground, airborne, and satellite observations. *Remote Sens. Environ.* 188, 127-140.

21. Meyer, C. *et al.* (2015) Global priorities for an effective information basis of biodiversity distributions. *Nat. Comm.* 6, 8221.

22. Kellner, J.R. *et al.* (2019) New Opportunities for forest remote sensing through ultra-high-density drone lidar. *Surv. Geophys.* 40, 959-977.

23. Almeida, D.R.A., et al. (2019) Monitoring the structure of forest restoration plantations with a drone-lidar system. *Int. J. Appl. Earth Obs.* 6379, 192-198.

24. Geijzendorffer, I.R. *et al.* (2017) How can global conventions for biodiversity and ecosystem services guide local conservation actions? *Curr. Opin. Environ. Sust.* 29, 145-150.

25. Duvall, M.S. *et al.* (2019) Collapsing complexity: Quantifying multiscale properties of reef topography. *J. Geophys. Res. Oceans* 124, 5021-5038.

26. Fahey, R.T. *et al.* (2019) Defining a spectrum of integrative trait-based vegetation canopy structural types. *Ecol. Lett.* 22, 2049-2059.

27. Silva, C.A. *et al*. (2020) rGEDI: NASA's Global Ecosystem Dynamics Investigation (GEDI) Data Visualization and Processing. R package version 0.1.2 .

28. Gallagher, R.V. et al. (2020) Open Science principles for accelerating trait-based science across the Tree of Life. *Nature Ecology & Evolution* .

29. Guo, X, *et al*. (2017) Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. *Ecol. Infor.* 38, 50-61.

30. Gough, C.M. *et al.* (2019) High rates of primary production in structurally complex forests. *Ecology* 100, e02864.

31. Milanesi, P. *et al.* (2017) Three-dimensional habitat structure and landscape genetics: A step forward in estimating functional connectivity. *Ecology* 98, 393-402.

32. Gwenzi, D. and Lefsy, M.A. (2014) Modeling canopy height in a savanna ecosystem using spaceborne lidar waveforms. *Remote Sens. Environ.* 154, 338-344.

33. Lopatin, J. *et al.* (2016) Comparing Generalized Linear Models and random forest to model vascular plant species richness using LiDAR data in a natural forest in central Chile. *Remote Sens. Environ.* 173, 200-210.

34. Marselis, S.M. *et al.* (2018) Distinguishing vegetation types with airborne waveform lidar data in a tropical forest-savanna mosaic: A case study in Lopé National Park, Gabon. *Remote Sens. Environ.* 216, 626-634.

35. Valbuena, R. *et al.* (2017) Key structural features of Boreal forests may be detected directly using L-moments from airborne lidar data. *Remote Sens. Environ.* 194, 437-446.

36. Zellweger, F. *et al.* (2016) Environmental predictors of species richness in forest landscapes: abiotic factors versus vegetation structure. *J. Biogeogr.* 43, 1080-1090.

37. Sankey, J.B. *et al.* (2015) Remote sensing of Sonoran Desert vegetation structure and phenology with ground-based LiDAR. *Remote Sens.-Basel* 7 ,342-359.

38. Ferreira, ME, et al. (2019) Monitoring the Brazilian savanna with lidar and RGB sensors onboard remotely piloted aircraft systems. *IEEE Int. Geosci. Remote Sens. Sym.* 9240-9243.

39. Coops, N.C. *et al.* (2016) A forest structure habitat index based on airborne laser scanning data. *Ecol. Ind.* 67, 346-357.

40. Asner, G.P. and Mascaro, J. (2014) Mapping tropical forest carbon: Calibrating plot estimates to a simple LiDAR metric. *Remote Sens. Environ.* 140, 614-624.

41. Adnan, S. et al. (2019) A simple approach to forest structure classification using airborne laser scanning that can be adopted across bioregions. *For. Ecol. Manage.* 43, :111-121.

42. Qi, W. and Dubayah, R.O. (2016) Combining Tandem-X InSAR and simulated GEDI lidar observations for forest structure mapping. *Remote Sens. Environ.* 187, 253-266.

43. Disney, M. *et al*. (2019) Innovations in ground and airborne technologies as reference and for training and validation: Terrestrial Laser Scanning (TLS). *Surv Geophys* 40, 937-958.

44. Bush, A. *et al.* (2017) Connecting Earth observation to high-throughput biodiversity data. *Nat. Ecol. Evol.* 1,0176.

45. Vihervaara, P. *et al.* (2015) How to integrate remotely sensed data and biodiversity for ecosystem assessments at landscape scale. *Landscape Ecol.* 30, 501-516.

46. Silva, C.A. *et al.* (2018) Comparison of small- and large-footprint lidar characterization of tropical forest aboveground structure and biomass: A case study from Central Gabon. *IEEE J. Sel. Top. Appl.* 11, 3512-3526.

47. Zhao, K. *et al.* (2018) Utility of multitemporal lidar for forest and carbon monitoring: Tree growth, biomass dynamics, and carbon flux. *Remote Sens. Environ.* 204, 883-897.

48. Cao, L. *et al.* (2016) Estimation of forest biomass dynamics in subtropical forests using multi-temporal airborne LiDAR data. *Remote Sens. Environ.* 178, 158-171.

49. Greaves, H.E. *et al.* (2015) Estimating aboveground biomass and leaf area of low-stature Arctic shrubs with terrestrial LiDAR. *Remote Sens. Environ.* 164, 26-35.

50. Thers, H. *et al.* (2017) Lidar-derived variables as a proxy for fungal species richness and composition in temperate Northern Europe. *Remote Sens. Environ.* 200, 102-113.

51. Moeslund, J.E. *et al.* (2019) Light detection and ranging explains diversity of plants, fungi, lichens, and bryophytes across multiple habitats and large geographic extent. *Ecol. Appl.* 29, e01907.

52. Davies, A.B. *et al.* (2017) Canopy structure drives orangutan habitat selection in disturbed Bornean forests. *Proc. Natl. Acad. Sci. USA* 114, 8307-8312.

53. Ferrari, R. *et al.* (2018) Habitat structural complexity metrics improve predictions of fish abundance and distribution. *Ecography* 41, 1077-1091.

54. Abelleira Martínez, O.J. *et al.* (2016) Scaling up functional traits for ecosystem services with remote sensing: concepts and methods. *Ecol. Evol.* 6, 4359-4371.

55. Mononen, L. *et al.* (2018) Usability of citizen science observations together with airborne laser scanning data in determining the habitat preferences of forest birds. *For. Ecol. Manage.* 430, 498-508.

56. Matasci, G. *et al.* (2018) Three decades of forest structural dynamics over Canada's forested ecosystems using Landsat time-series and lidar plots. *Remote Sens. Environ.* 216, 697-714.

57. Almeida, D.R.A. *et al.* (2019) A new era in forest restoration monitoring. *Restor. Ecol.* 28, 8-11.

58. Lucas, R. *et al.* (2020) Structural characterisation of mangrove forests achieved through combining multiple sources of remote sensing data. *Remote Sens. Environ.* 237, 111543.

59. Smith, M.N. *et al.* (2019) Seasonal and drought-related changes in leaf area profiles depend on height and light environment in an Amazon forest. *New Phytol.* 222, 1284-1297.

60. Fisher, R.J. *et al.* (2018) A novel technique using LiDAR to identify native-dominated and tame-dominated grasslands in Canada. *Remote Sens. Environ.* 218, 201-206.

61. Maguire, A.J. *et al.* (2019) Terrestrial lidar scanning reveals fine-scale linkages between microstructure and photosynthetic functioning of small-stature spruce trees at the forest-tundra ecotone. *Agric. For. Meteorol.* 269-270, 157-168.

62. Turak, E. *et al.* (2017) Essential Biodiversity Variables for measuring change in global freshwater biodiversity. *Biol. Conserv.* 213, 272-279.

63. Shao, G. *et al.* (2019) Towards high throughput assessment of canopy dynamics: The estimation of leaf area structure in Amazonian forests with multitemporal multi-sensor airborne lidar. *Remote Sens. Environ.* 221, 1-13.

64. Hilmers, T. *et al.* (2018) Biodiversity along temperate forest succession. *J. Appl. Ecol.* 55, 2756-2766.

65. Scaranello, M.A.S. *et al.* (2019) Estimation of coarse dead wood stocks in intact and degraded forests in the Brazilian Amazon using airborne lidar. *Biogeosciences* 16, 3457-3474.

66. McCarley, T.R. *et al.* (2017) Multi-temporal LiDAR and Landsat quantification of fire-induced changes to forest structure. *Remote Sens. Environ.*191, 419-432.

67. Hu, T. *et al.* (2019) A simple and integrated approach for fire severity assessment using bi-temporal airborne LiDAR data. *Int. J. Appl. Earth Obs.* 6378, 25-38.

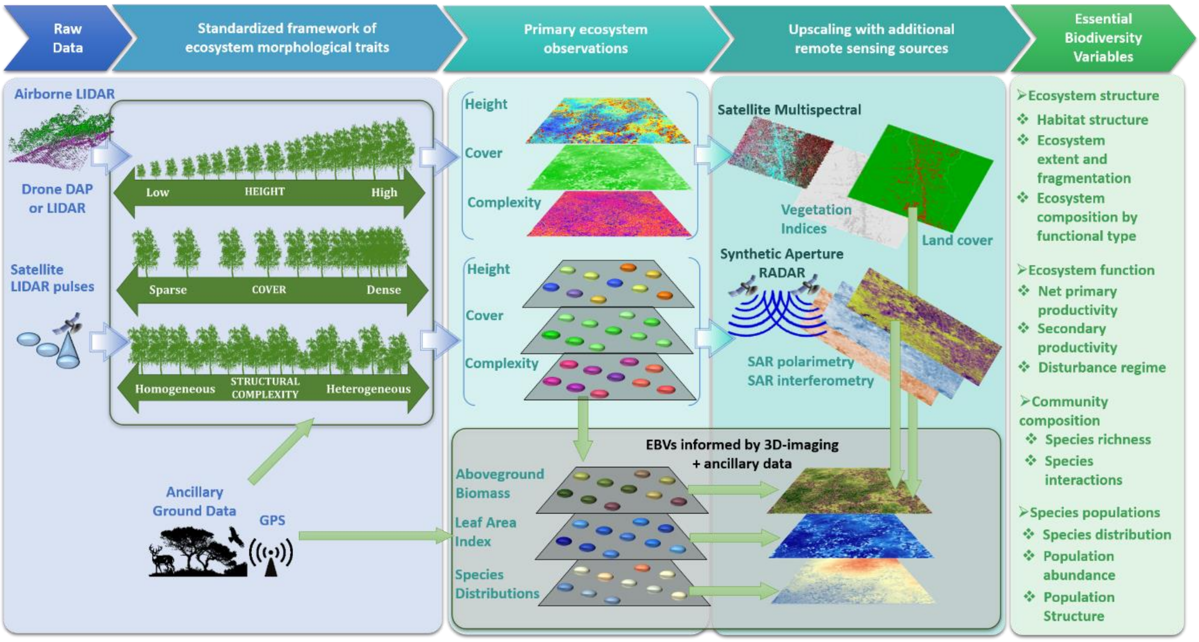
68. Duncanson, L. and Dubayah, R.O. (2018) Monitoring individual tree-based change with airborne lidar. *Ecol. Evol.* 8, 5079-5089.

69. Reddy, A.D. *et al.* (2015) Quantifying soil carbon loss and uncertainty from a peatland wildfire using multi-temporal LiDAR. *Remote Sens. Environ.* 170, 306-316.

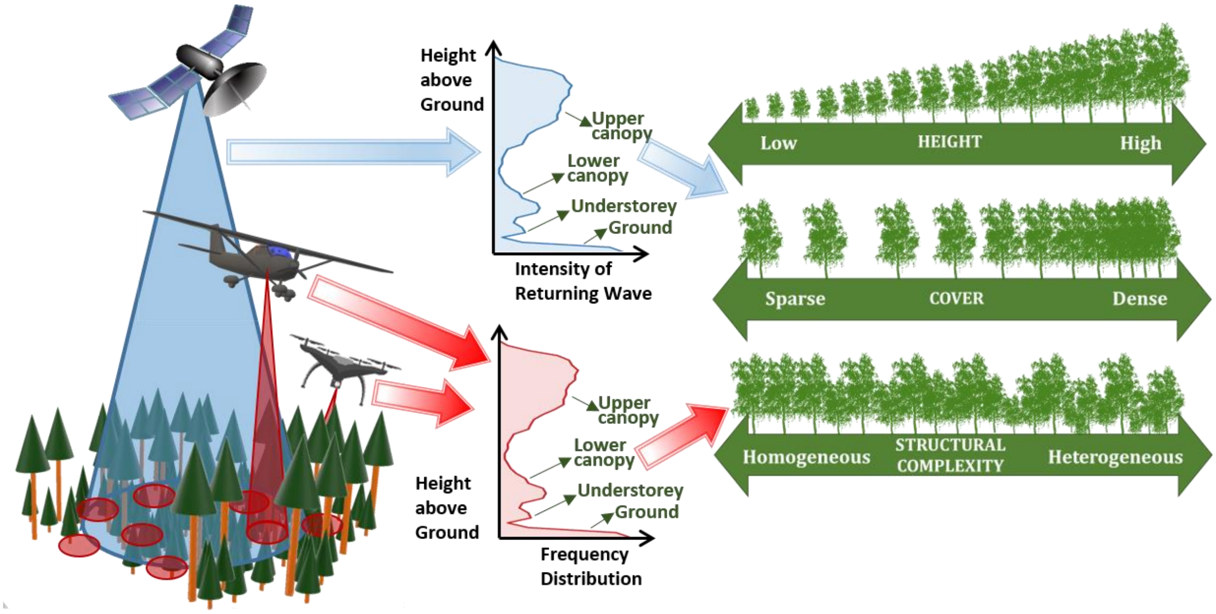
70. Song, Y. *et al.* (2016) Estimation of broad-leaved canopy growth in the urban forested area using multi-temporal airborne LiDAR datasets. *Urban For. Urban Gree.* 16, 142-149.

FIGURES

Figure. 1. Schematic diagram showing the practical pathways for deriving EBVs from various potential sources, using a framework of standardised ecosystem morphological traits derived from 3D-imaging and/or ground information.



Box 1, Figure I. Basic common procedures for deriving morphological traits from different 3D-RS data sources. Satellite LIDAR provides discretely-spaced pulses with a large footprint, whereas 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.



TABLES

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.

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**	
Core traits (measured)																
Ecosystem structure / Habitat structure and condition	Height	[39]	[38]	[32]	[58]	[56]	[14]	[37]	[40]		[42]	[42]				Top or average height above ground.
	Cover	[36]			[58]	[56]					[4]		[4]			Proportion of heights above thresholds. Estimates of LAI or gap fraction using ground data for calibration.
	Structural Complexity	[35]	[53]			[65]		G3D [23]	[26]	[16]	[42]	[42]			G3D	Variability of LIDAR heights (rugosity), or leaf area density profiles. Estimates of biomass distribution using ground data for calibration.
Derived traits (estimated)																
Ecosystem structure / Ecosystem extent and fragmentation	Habitat area	[39]						[37]					[1]			Area under certain characteristics, e.g. vegetation cover above threshold
	Habitat connectivity and fragmentation	[31]														Combination: vegetation height, cover and vertical structure
Ecosystem Function	Carbon sequestration	[40]		[46]	[58]			G3D [49]	[20]		[20]			[20]	G3D [43]	Estimates of above (or below) ground biomass using ground data for calibration

	Decomposition	[65]											Estimates of coarse woody debris using ground data for calibration
	Disturbance regime	[67]		[66]									Area affected by disturbances
Ecosystem composition / Taxonomic diversity	Species diversity / Richness	[33]				HS [13]	[15]		[3]	[44]		HS [15]	Estimates of alpha/beta diversity and richness using presence/absence data for calibration
Species populations	Species distributions	[52]			[55]	[37]	[51]				[8]		Estimates of habitat suitability for species using presence/absence data for calibration
	Population abundance / Ecosystem classes	[29]											Combinations of vegetation height, cover and structural complexity. Estimates of ecosystem classes using ground data for calibration
	Population structure by size class	[55]				G3D [61]	[38]					G3D	Combination of estimates of biomass and species distribution using ground data for calibration.

ALS: airborne LIDAR; **DAP**: digital aerial photogrammetry; **SatL**: satellite LIDAR; **MS**: satellite multispectral; **HS**: hyperspectral; **SAR**: satellite synthetic aperture radar; **Field**: field data acquired on the ground; **G3D**; ground-based 3D-imaging (e.g. terrestrial LIDAR or proximal photogrammetry).

Table 1 Legend:

(green)	Required: this data type alone could suffice for the retrieval of an EBV at national/global scale .
(purple)	Required in combination: this data type requires combinations with other data sources for the retrieval of an EBV at national/global scale. See the publications cited for examples and details.
(yellow)	Useful but not required: while not essential, this data type can be helpful in improving the retrieval of an EBV from other data sources at national/global scale.

	Not required: this data is not informative for a given EBV, or the EBV can be more optimally attained from other data sources.

Table 2. Recent 3D-RS studies on ecosystem structure for worldwide dominant vegetation types and/or involving change detection.

Vegetation type	**Reference**	**System**	**Multi-temporal**	**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
Sub-tropical 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
	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 topo-hydrographic LIDAR	No	Ecosystem structural complexity
Urban forests	Song et al. [70]	Airborne laser scanning	2004-2008-2010	Change in vegetation height

492

TEXT BOXES

Box 1. 3D-imaging data sources: current availability and feasibility for assessing EBVs

Satellite and airborne sources of 3D-imaging, both 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.

***** approximate position of Figure I *****

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 – three years for ICESat-2 and two 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 51.6º 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 difficult to assess ecosystem traits involving neighbouring analyses, such as ecosystem extent and fragmentation (**Table 1**). GEDI datasets [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] (**Fig. 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].

Airborne Laser Scanning (ALS):

Several national / regional surveying programmes are producing ALS datasets covering entire countries (**Table II**), many of them with revisited coverages. These low-density datasets (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 datasets [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 (2019) [19] processing steps to facilitate the homogenization of disparate airborne acquisition settings.

Box 1 Table I. Satellite missions that may be used to support ecosystem structure assessments (**Fig. 1**) towards the UN Agenda's 2030 Sustainable Development Goals.

Sensor	Satellite / Programme	Agency	Starting from Year	Link
LIDAR	Global Ecosystem Dynamics Investigation (GEDI)	NASA	2018	

	Ice, Cloud and land Elevation Satellite-2 (ICESat-2)	NASA	2018	
Optical	Earth Observing System (Landsat, MODIS, etc)	NASA	1972	
	Copernicus Global Monitoring (Sentinel)	ESA	2014	
	High-Definition Earth Observation Sat. (HDEOS)	CNSA	2015	
SAR	BIOMASS	ESA	2021	
	Phased Array type L-band SAR (PALSAR)	JAXA	2006	
	NISAR	NASA-ISRO	2022	
	TanDEM-X	DLR	2014	
	TanDEM-L	DLR	2022	
	Shuttle Radar Topography Mission (SRTM)	International	2000	

NASA: US National Aeronautics and Space Administration; **ESA**: European Space Agency; **CNSA**: China National Space Administration; **JAXA**: Japan Aerospace Exploration Agency; **ISRO**: Indian Space Research Organization; **DLR**: German Aerospace Center

Box 1 Table II. Examples of publicly available airborne ALS datasets from national / regional surveying programmes.

Country / State	**Agency / Programme**	**Link**
Canada	Agriculture and Agri-Food Canada	
Australia	GeoScience Australia &Terrestrial Environ. Research Network	
Denmark	Kortforsyningen	
Finland	Maanmittauslaitos / National Land Survey of Finland (NLSF)	
Germany / North Rhine-Westphalia (NRW)	OpenNRW	
Netherlands	Actueel Hoogtebestand Nederland (AHN)	
Spain	Instituto Geográfico Nacional (IGN) / Plan Nacional de Ortofotografía Aérea (PNOA)	

United Kingdom	UK Environment Agency
United States of America	US Geological Survey (USGS). US Department of Interior

GLOSSARY

- **3D-imaging**: Also known as 3D remote sensing, the concept includes any RS method that detect 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, understorey vegetation, and the ground (**Box 1 Figure I**). 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 popularised structure-from-motion (SfM) methods which deliver dense DAP data.
- **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 cover**: Percentage of a fixed area covered by the vertical projection the ecosystem **structural elements**. Common terms employed for vegetation is plant area index [13,34], or colony cover for corals [16].
- **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].
- **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 (**Box 1 Figure I**). Nonetheless, the information can be similarly utilised 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 rain forests and mountainous regions. Depending the wavelength (e.g. C-band or L-band) different ecological features can be recognised.

HIGHLIGHTS

- 3D-imaging data acquired from a variety of platforms has become critical for ecological and environmental management. However, the use of disparate information sources to produce comprehensive and standardised global products is hindered by a lack of harmonisation 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.

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 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 co-registration errors?
- How can changes in these ecosystem structure components be relevant to biodiversity conservation policy and practice? How can the global community of remote sensing 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.
- 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, e.g. by providing cover from predators or providing nesting or hibernating sites. The disaggregation into

ecosystem structure components may enable us to analyse 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?