Harmonised airborne laser scanning products can address the limitations of large-scale spaceborne vegetation mapping

Vítězslav Moudrý[1], Ruben Remelgado[2], Matthias Forkel[3], Michele Torresani[4], Gaia Vaglio Laurin[5], Eliška Šárovcová[1], Virginia E. Garcia Millan[6], Fabian Jörg Fischer[7,8], Tommaso Jucker[7], Michal Gallay[9], Patrick Kacic[10], Christopher R. Hakkenberg[11], Žiga Kokalj[12], Krzysztof Stereńczak[13], Yousef Erfanifard[14,15], Duccio Rocchini[16,1], Jiří Prošek[1], Stephanie Roilo[2], Kateřina Gdulová[1], Anna F. Cord[2], Michela Perrone[1], Juan Alberto Molina-Valero[1], Peter Surový[17], Zlatica Melichová[17], Marco Malavasi[18], Rudolf Urban[19], Martin Štroner[19], Dominik Seidel[20], Szilárd Szabó[21], László Bertalan[21], Anette Eltner[3], Roberto Cazzolla Gatti[16], Vojtěch Barták[1]

[1] Department of Spatial Sciences, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Praha – Suchdol, 165 00, Czech Republic

[2] Agro-Ecological Modeling Group, Institute of Crop Science and Resource Conservation, University of Bonn, Germany

[3] TUD Dresden University of Technology, Faculty of Environmental Sciences, Institute of Photogrammetry and Remote Sensing, Helmholtzstraße 10, 01069 Dresden, Germany

[4] Free University of Bozen/Bolzano, Faculty of Agricultural, Environmental and Food Sciences, Piazza Universitá/Universitätsplatz 1, 39100, Bozen/Bolzano, Italy

[5] Research Institute on Terrestrial Ecosystems, National Research Council, Montelibretti Research Area, Via Salaria Km 29,300, 00015 Montelibretti, RM, Italy

[6] Khaos Research. Institute of Software Technology and Engineering (ITIS). University of Malaga. C. Arquitecto Francisco Peñalosa, 18, 29010, Málaga Spain

[7] School of Biological Sciences, University of Bristol, Bristol, UK

[8] TUM School of Life Sciences, Ecosystem Dynamics and Forest Management, Technical University of Munich, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany

[9] Institute of Geography, Faculty of Science, Pavol Jozef Šafárik University in Košice, Jesenná 5, 040 01 Košice, Slovakia

[10] University of Würzburg, Institute of Geography and Geology, Department of Remote Sensing, Am Hubland, 97074 Würzburg, Germany

[11] School of Informatics, Computing & Cyber Systems, Northern Arizona University, Flagstaff, AZ 86011 USA

[12] Research Centre of the Slovenian Academy of Sciences and Arts, Ljubljana, Slovenia

[13] Department of Geomatics, Forest Research Institute, Braci Leśnej 3 Street, Sękocin Stary, 05-090 Raszyn

[14] Department of Remote Sensing and GIS, College of Geography, University of Tehran, Tehran, Iran

[15] IDEAS NCBR Sp. z o.o., Ul. Chmielna 69, Warsaw 00-801, Poland

[16] BIOME Lab, Department of Biological, Geological and Environmental Sciences, Alma Mater Studiorum University of Bologna, via Irnerio 42, 40126, Bologna, Italy

[17] Faculty of forestry and wood science, Czech University of Life Sciences Prague, Kamýcká 129, Praha – Suchdol, 165 00, Czech Republic

[18] Department of Chemistry, Physics, Mathematics and Natural Sciences, University of Sassari, Sassari, Italy

[19] Department of Special Geodesy, Faculty of Civil Engineering, Czech Technical University in Prague, Thákurova 7, 166 29 Prague 6, Czech Republic

[20] Department for Spatial Structures and Digitization of Forest, Faculty of Forest Sciences and Forest Ecology, Georg August University of Göttingen, Büsgenweg 1, 37077 Göttingen

[21] Department of Physical Geography and Geoinformatics, Faculty of Science and Technology, University of Debrecen, Egyetem tér 1., 4032 Debrecen, Hungary

Author contact: Vitezslav Moudry, moudry@fzp.czu.cz

This manuscript is a non-peer-reviewed preprint submitted to EarthArXiv.

December 3, 2024

Abstract

Vegetation structure data are essential for understanding the functioning of terrestrial ecosystems and for informing various science-policy interfaces. Recent years have seen a growing demand for high-resolution data on vegetation structure, driving the prediction of such metrics at fine resolutions (1 m - 30 m) at state, continental, and global scales by combining satellite data with machine learning. As these initiatives expand, it is crucial for the remote sensing and ecological communities to actively discuss the quality and usability of these products. Here, we (i) provide a brief overview of space-borne lidar missions measuring vegetation structure; (ii) using global canopy height models (CHMs) as an example, we demonstrate that predicted products exhibit significant errors exceeding natural changes in canopy height observed over a 10-year period, indicating that even a 10-year-old CHM derived from airborne laser scanning (ALS) is superior to currently available predicted CHMs; therefore, (iii) we recommend that regions with abundant ALS data prioritize harmonizing ALS-based vegetation metrics rather than relying solely on much less accurate predicted products derived from satellite data. We investigated the availability of ALS data in Europe and found that they are available for 26 countries, collected mostly between 2009 and 2024. We argue that, despite variations in data characteristics, including temporal inconsistencies and differences in point density and classification accuracy, the production of vegetation structure metrics, particularly CHMs, in raster format at fine resolution is both necessary and feasible. As new acquisitions are planned or underway, it is important to coordinate efforts to facilitate harmonization, develop continent-wide products, and ensure free access for research and policy communities. Beyond numerous ecological applications, such consistent benchmark datasets are crucial for calibrating future Earth Observation missions, making them essential for producing truly global, fine-resolution vegetation structure data.

Keywords

Canopy, Earth observation, Forestry, Lidar, Validation, Vegetation structure

1. Introduction

Ecosystem structure – the spatial arrangement of biotic and abiotic elements that make up an ecosystem – is an Essential Biodiversity Variable (EBV) considered critical for understanding ecosystem function (Skidmore et al. 2021). In terrestrial ecosystems, the vegetation structure – the horizontal and vertical distribution of vegetation – is the key component. Vegetation structure plays a crucial role in modulating multiple ecosystem processes. In particular, it regulates energy flow, water cycling, carbon sequestration, and primary productivity (Murphy et al. 2022; LaRue et al. 2023a; Li et al. 2024). Furthermore, vegetation structure creates unique habitats that support species coexistence across different layers of vertical profile of the vegetation (Davies and Asner 2014; Moudrý et al. 2021; Wildermuth et al. 2023; Kemppinen et al. 2024). The prevailing theory is that structurally complex vegetation stands are more effective at optimizing the incoming light and water resources, leading to better carbon assimilation (Atkins et al. 2018; Seidel and Ammer 2023), and that they provide a greater number of ecological niches, thereby enhancing biodiversity (Tews et al. 2004; Stein et al. 2014; Torresani et al. 2020; Coverdale and Davies 2023).

Remote sensing technologies such as Light Detection and Ranging (lidar) have played a key role in addressing knowledge gaps, providing a way to accurately map vegetation structure from local to global scales (Herold et al. 2019; Valbuena et al. 2020; Jutras-Perreault et al. 2023; Liu et al. 2023; Moudrý et al. 2023; Rosen et al. 2024). Particularly, lidar sensors onboard planes (i.e., airborne laser scanning; ALS) have considerably advanced national monitoring programs (e.g., Assmann et al. 2022; Kissling et al. 2023) and robust approaches to convert ALS data into structural metrics are available (Fischer et al. 2024). However, while the costs of ALS have decreased in recent years, large continuous coverage exists only in a few regions, mostly in Europe, North America, and Australia, as well as countries such as New Zealand and Japan, and only a few countries have mapped their entire territory more than once.

Recent advances in space-borne lidar missions, such as Global Ecosystem Dynamics Investigation (GEDI) and the Ice, Cloud, and land Elevation Satellite-2 (ICESat-2), help address the spatial and temporal limitations of ALS data (Markus et al. 2017; Dubayah et al. 2020). These missions provide free data that have enabled the creation of global models of vegetation structure (e.g., Mulverhill et al. 2022; Burns et al. 2024), supporting innovative and impactful research. For instance, vegetation structure products derived from space-borne lidar data have been used to monitor forest/woodland structure and regrowth (Milenković et al. 2022; Jucker et al. 2023; Stritih et al. 2023), track carbon losses from disturbances (Holcomb et al. 2024), evaluate the effectiveness of protected areas from the perspective of carbon stocks and vegetation structure (Ceccherini et al. 2023; Lang et al. 2023;

Liang et al. 2023, Brodie et al. 2023), and to assess species diversity and species-environment relationships (Marselis et al. 2022; Smith et al. 2022; Vogeler et al. 2023; Xu et al. 2024). However, space-borne lidar data are spatially and temporally limited, and their derived products, such as global canopy height models (CHMs), suffer from accuracy issues (Mandl et al. 2023; Moudry et al. 2024), which impair their applicability (Hakkenberg et al. 2023).

Consistent data on vegetation structure is essential for informing multiple science-policy interfaces. For instance, the Ecosystem Vertical Profile, which refers to the vertical distribution of biomass, is one of the 21 EBVs defined by the Group on Earth Observations Biodiversity Observation Network (Pereira et al. 2013), setting key data requirements for global, UN-level, biodiversity change monitoring and reporting (e.g., in the scope of Global Biodiversity Observing System, GEO BON 2022). Vegetation structure data also support the United Nations' System of Environmental-Economic Accounting (United Nations 2021, 2022) and play a role in tracking progress toward Global Biodiversity Framework targets (Skidmore et al. 2021). Additionally, such data are vital for assessing restoration success, as emphasized in the Nature Restoration Law and EU Forest Strategy for 2030 (Ruiz-Jaen and Adie 2005; LaRue et al. 2023b).

As new mapping and modeling initiatives develop data products on vegetation structure to meet the monitoring needs of emerging science-policy interfaces, it is crucial for the remote sensing and ecological communities to actively discuss the usability of these products and establish plans to measure, avoid, and correct their limitations. In this article, we aim to (i) provide a brief overview of space-borne lidar missions that measure vegetation structure, (ii) examine the limitations of these data, using CHMs as a case study, and (iii) propose a path toward improving continental and global CHMs through the harmonisation of airborne laser scanning products.

2. Mapping vegetation structure with space-borne lidar

Details and examples of the usability and advantages of lidar remote sensing for mapping vegetation structure can be found in Lefsky et al. (2002), Bergen et al. (2009), and Moudrý et al. (2023). Simply put, lidar is ideal for measuring vegetation structure because it can penetrate through the gaps in the vegetation, capturing its vertical structure as well as the shape of the terrain underneath. Lidar sensors can be installed on various platforms, including tripods, backpacks, cars, drones, helicopters, planes, and satellites. Notably, space-borne lidar is especially valuable for large-scale mapping due to its consistent and extensive global coverage. Satellite sensors are expected to become the primary data source for mapping the vegetation structure in response to international monitoring requirements.

Yet, technical issues concerning data coverage and accuracy persist (Hancock et al. 2021; Liu et al. 2021).

The first global dataset characterizing canopy structure was obtained from the Geoscience Laser Altimeter System (GLAS) onboard the Ice, Cloud, and land Elevation Satellite (ICESat), operational from 2003 to 2009 (Abshire et al. 2005). This mission was primarily intended for measuring polar ice caps but it also enabled the development of datasets for ground elevation and canopy height (Schutz et al. 2005; Simard et al. 2011). In 2018, NASA launched two space-borne lidar missions, ICESat-2 (Markus et al. 2017) and GEDI (Dubayah et al. 2020), aimed among other objectives at providing global data on terrain and canopy height.

A major limitation of space-borne lidar sensors is that they collect data along discrete transects, providing discrete and dislocated sample data of vegetation structure. Additionally, various factors, including atmospheric conditions, solar background photons, laser pulse energy, and topography, affect data accuracy and require filtering, resulting in significant reductions in available data (e.g. Hayashi et al. 2013; Moudrý et al. 2022; 2024b). Although current lidar space-borne missions have substantially higher sampling densities than their predecessors, the data are still insufficient for producing high-resolution continuous CHMs, and the derived data products have limited spatial and temporal coverage. For instance, GEDI was expected to sample only 4% of the Earth's land surface over a two-year mission, enabling the production of a near-global (from -52° to 52° latitude) vegetation structure metrics, including CHM at three spatial resolutions: 1 km, 6 km, and 12 km (Burns et al. 2024). A global-scale 1 km resolution canopy model is a significant achievement but has limited utility for applications such as ecosystem mapping or species-environment relationship assessments, which typically require finer resolution (Smith et al. 2022; Anderle et al. 2023; Davison et al. 2023; Vogeler et al. 2023).

A potential solution to provide global fine-resolution data on the vertical structure of vegetation for the entire world at a reasonable cost could lie in the creation of a fleet of lidar satellites that would continuously map the Earth (Hancock et al. 2021; Lowe et al. 2024). Hancock et al. (2021) estimated that producing such continuous data at a 30 m resolution every 5 years would require a constellation of twelve satellites acting concurrently. More recently, Lowe et al. (2024) investigated which platform-optics-constellation design combination offers the most promising and cost-effective solution, and suggested that micro-satellites, with a mass on the order of 150 kg, may present the most attractive performance-to-cost ratio. They estimated that a constellation of eight such satellites would be sufficient to produce CHMs at a 20-meter resolution annually. In addition, NASA currently has an advanced proposal for the next-generation space-borne laser altimetry mission, known as Earth

Dynamics Geodetic Explorer (EDGE), which aims to significantly improve spatial and temporal coverage. At present, however, such satellite systems do not exist, and an operational mission capable of delivering higher-resolution global lidar data is unlikely before 2030. Hence, in the meantime, alternative solutions must be explored to meet immediate monitoring needs.

3. Predicted continuous high-resolution CHMs and their limitations

The lack of global high-resolution data on vertical vegetation structure has stimulated the use of space-borne lidar data in combination with other satellite products to generate predicted models of vegetation structure variables, such as canopy height, total canopy cover, and foliage height diversity at fine resolutions, such as 10 m or 30 m (e.g., Kacic et al. 2021, 2023; Schwartz et al. 2023; Diaz-Kloch and Murray 2024). A common approach to produce the high resolution, wall-to-wall data on vegetation structure is to train predictive models that combine direct but discrete height measurements (e.g., from space-borne lidar ICESat, GEDI, ICESat-2) with spatially continuous data (e.g., from space-borne optical and radar data). The model establishes a relationship between the discrete and the continuous data that enables the estimation of the height at locations not directly measured by lidar (Bergen et al. 2009; Lefsky 2010). Predicted CHMs are among the most common and, so far, the only high-resolution vegetation structure products available at continental (Liu et al. 2023) and global scales (Potapov et al. 2021; Lang et al. 2023), making them suitable for illustrating the pros and cons of such data. Recently, a web application has been developed, making this approach easily accessible (Alvites et al. 2024).

Several continental or global predicted CHMs have been produced. The first such dataset was developed by Lefsky (2010), who combined canopy heights derived from GLAS with MODIS data to produce a patch-based global CHM. Similarly, Simard et al. (2011) used the relationships between the GLAS-derived canopy heights and multiple environmental variables (e.g., tree cover, climate, altitude) to predict a global model of canopy heights at a 1 km spatial resolution. Recently, Potapov et al. (2021) and Lang et al. (2023) used optical satellite data (Landsat, Sentinel-2) trained on GEDI measurements to create global CHMs at 30 m and 10 m spatial resolutions, respectively. Likewise, Liu et al. (2023) used canopy height from airborne laser scanning (ALS) data and PlanetScope imagery to predict canopy heights in Europe at the 3 m resolution. Finally, Meta, in cooperation with the World Resources Institute, combined high-resolution data from optical satellites, ALS, and GEDI to develop a global CHM at a 1 m resolution (Tolan et al. 2024).

The main benefit of predicted CHMs based on space-borne lidar lies in their easy availability, especially as there are no alternatives at scales beyond the regional level. These CHMs are usually readily available as open data in a raster format, allowing researchers to use them as input data in common GIS software to inform their analyses. This contrasts with the high data volume, time-consuming, and often challenging process of working with more accurate ALS point clouds, which can be difficult for many ecologists to store and handle (Moudrý et al. 2023; Kissling and Shi 2023; Wang et al. 2024). However, the easy accessibility of such predicted CHMs is both a blessing and a curse as users may be unaware of data limitations, and the reliability of predicted global datasets is questionable (Duncanson et al. 2019; Meyer and Pebesma 2022). Modeling canopy height is a complex process that involves errors and biases from multiple sources, ranging from ground detection with space-borne lidar to the saturation of optical data in closed-canopy forests. Indeed, independent validation studies showed that the accuracy of these satellite-derived global CHMs is low (e.g., Bolton et al. 2013; Pascual et al. 2022), and their use in biodiversity modeling leads to erroneous results (Moudrý et al. 2024a).

3.1 Validation of predicted global CHMs accuracies

Here we evaluate four recent predicted CHMs (Table 1). We used a 2022 ALS scan from the Giant Mountains National Park (Czechia) as a reference and compared it both to satellite-derived height models and to a second ALS scan acquired 10 years earlier, in 2012 (all ALS data were processed with standard methods, cf. Moudrý et al. 2024a). Strikingly, we found that the 2012 ALS data had a much lower error in predicting 2022 canopy height than any of the global or regional CHMs. Figure 1 presents a cross-section comparison of vegetation heights extracted from four predicted space-borne data-based CHMs to reference heights extracted from ALS CHMs. Both large over- and underestimation of vegetation height can be observed in space-borne CHMs (Figure 1; see Moudrý et al. (2024a) for comparison across more sites). Moreover, the change in vegetation height over ten years is lower than the canopy height error in the four models for the selected area (Figure 2). In this specific case study, such an error hinders effective change detection analyses on the canopy height. This limitation is influenced by the magnitude of disturbance, which is relatively low in our study area (Figure 2). In cases of large-scale deforestation detectable by optical data, the signal should still be visible in predicted CHMs. However, to estimate changes in vegetation height accurately, we must first know the height before such disturbances occur.

3.2 What to report and consider when generating and using CHMs

Global datasets are indispensable for answering large-scale ecological questions, so it is imperative to improve reporting of the accuracy and uncertainty of the predicted CHMs to enable users to easily select the most appropriate map for their purposes. To select the best vegetation structure product, the overall evaluation metrics, such as mean error (ME) or root mean square error (RMSE), provided by existing products are fundamental, despite providing a limited insight into the local map quality. Even if the user selects the most accurate map (i.e. that with the lowest overall RMSE), there may be considerable biases in the subregions. However, these uncertainties are usually not quantified; if they are, it is often unclear how this was done (but see Lang et al. 2023) or the uncertainty estimates are inaccurate (Moudrý et al. 2024a). One way to improve the reporting of uncertainties is to assess the area to which a prediction can be reliably applied, such as estimating the Area of Applicability (Meyer and Pebesma 2021). Furthermore, we suggest that in addition to the common validation using ALS data, the predicted CHM products should include representative profiles (as in Figure 1). Most authors of the global datasets only showed product visualizations in 2D space (e.g., Potapov et al. 2021; Lang et al. 2023; Schwartz et al. 2023). Even inaccurate CHM models look very plausible in a 2D visualization, and even an experienced user is easily misled into the false impression that they accurately represent the reality (Figure 2).

Table 1. Predicted global canopy height models (CHMs) evaluated in this study. The Root mean square error (RMSE) value reported by the authors of individual CHMs in the original publications is presented here.

Global CHM	Author	Resolution	RMSE	Valid for year
Global forest canopy height	Potapov et al. (2021)	30 m	9.1 m	2019
High-resolution canopy height model of the Earth	Lang et al. (2023)	10 m	2.8 - 9.6 m	2020
Canopy height map for Europe	Liu et al. (2023)	3 m	4.3 - 6.4 m	2019
Global map of tree canopy height	Tolan et al. (2024)	1 m	4.4 m	2018-2020

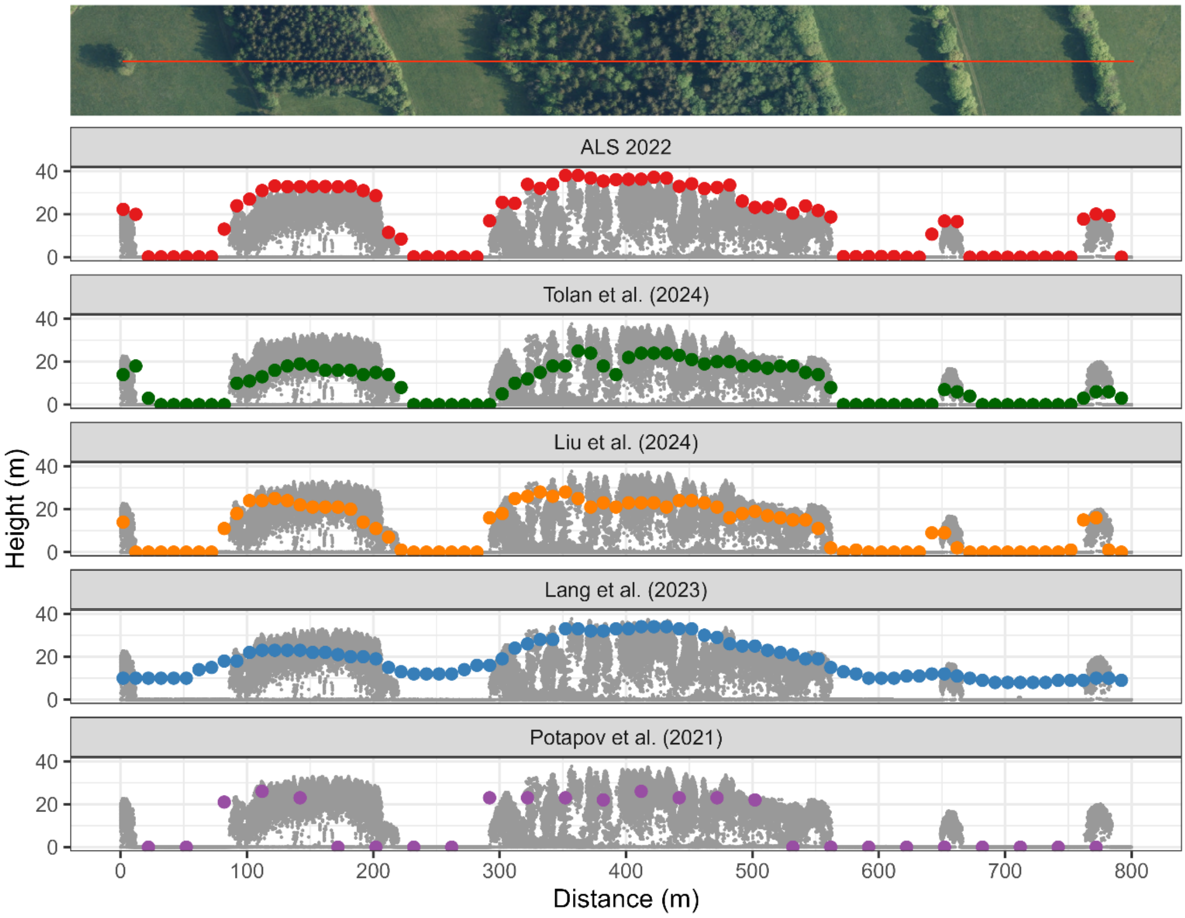

Figure 1. A representative canopy height profile from the Giant Mountains National Park, Czechia. The profile spans 10 meters in width. Note the limited ability, especially in the CHM by Lang et al. (2023), to capture variations in canopy height, making the transition between forest and non-forest areas unclear. The mosaic of pastures and forests appears as a continuous forest with heights ranging from 10 to 30 meters. In contrast, the CHMs by Tolan et al. (2024) and Liu et al. (2024) more effectively differentiate between forest and non-forest areas due to the substantially higher resolution of their input data. However, both CHMs tend to underestimate the height of vegetation. This suggests that there may be room for improvement in combining multiple predicted CHMs, such as the one by Tolan et al. (2024), which accurately distinguishes forests from non-forested areas, and the model by Lang et al. (2023), which is relatively successful in predicting top canopy height. The CHM by Potapov et al. (2021) has a resolution that is too coarse to capture smaller stands.

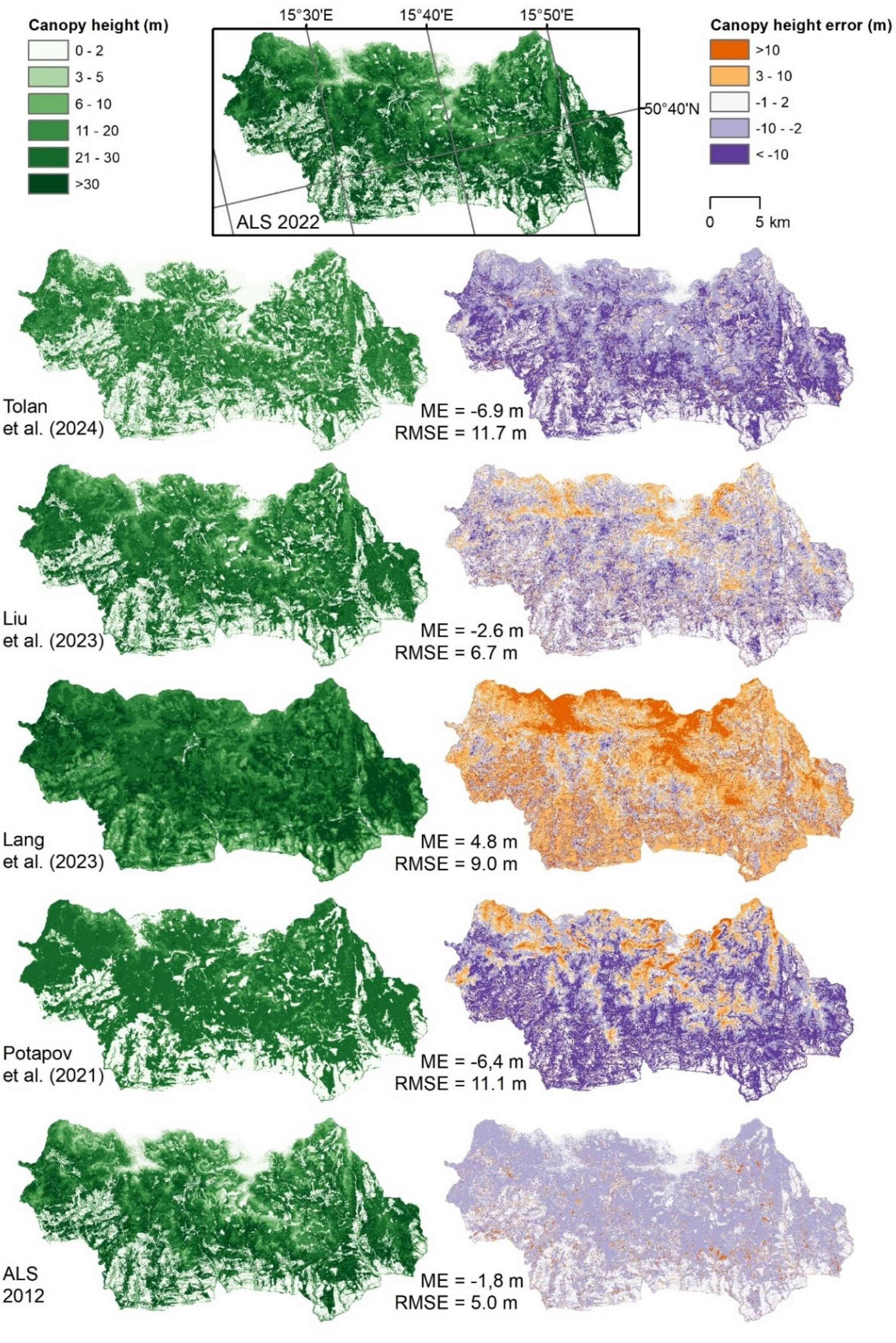

Figure 2. Canopy height from six different sources in the Giant Mountains National Park (Czechia). This includes airborne laser scanning (ALS) data from 2022 (reference dataset) and 2012, along with four predicted canopy height maps: Tolan et al. (2024), Liu et al. (2023), Lang et al. (2023), and Potapov et al. (2021). The figures on the left show canopy height, while the figures on the right show the difference in canopy height compared to the ALS 2022 data (i.e., the error of the predicted maps). ME stands for Mean Error, and RMSE stands for Root Mean Square Error.

4. Towards improved continental to global canopy height models

Unlike space-borne laser altimeters, which offer broader coverage but discrete and sparse measurement (Dubayah et al. 2020), ALS offers dense continuous coverage and is commonly used for regional or state-wide mapping. However, processing of ALS point clouds and their integration into a single product is challenging for larger-scale analyses covering multiple countries (Fischer et al. 2024). As a result, large-scale studies generally rely on global predicted products (see Section 3) due to the difficulties in managing and processing ALS data at a continental scale.

Even if we manage to build a satellite lidar system capable of dense spatio-temporal coverage in the near future (see Section 2), it will need precise and consistent benchmark datasets over broad geographical domain for its calibration. ALS data are indispensable for such a purpose (e.g. Duncanson et al. 2019; Tang et al. 2023). Moreover, knowing the current status of vegetation structure is essential, and such data will be useful for assessing changes in vegetation structure (Guerra-Hernández and Pascual 2021; Parra and Simard 2023). Therefore, locally available data should be used to produce uniform seamless vegetation structure products.

In the United States, the 3D Elevation Program (3DEP), managed by U. S. Geological Survey (USGS), has been launched, aiming to collect ALS data for conterminous United States. So far, however, it only aims at providing a digital terrain model (DTM; Stoker 2020; Stoker and Miller 2022), not seamless CHMs (or other vegetation structure products) in a raster format. Digital surface models (DSMs) can, however, be created through OpenTopography (https://opentopography.org/) where most U.S. lidar data are also hosted. Europe is further behind, as no common data collection protocol or methodology that regulates mapping activities exists. This responsibility falls onto its Member States. As a result, ALS coverage in Europe is managed at the national (e.g., in Denmark, France, Poland, Spain) or sub-national (e.g., in Austria, Belgium, Germany, Italy) level and data are scattered among providers, leading to different characteristics across regions (D'Amico et al. 2021; Kakoulaki et al. 2021).

Given the substantial investments required for country-wide ALS data acquisition, there is a clear need for continued efforts to ensure its effective use in vegetation mapping. Of the 44 countries in Europe, ALS data is collected by governmental institutions in at least 26 countries (Table 2). Although the data have different characteristics (such as point density and accuracy), it should be possible to derive vegetation structure characteristics in raster format at a relatively fine resolution. This, however, requires standardized processing pipelines that can account for differences in scanning properties (Fischer et al. 2024) and detailed documentation of the metadata, particularly regarding the acquisition time. However, metadata, if available, are documented with various degrees of depth and reliability, which significantly limits their accessibility and utility for potential users. For example, we made every effort to review the characteristics of ALS data available in Europe (Table 2), but we had to limit our focus to point density and the year of data acquisition. This was due to the difficulty of narrowing down the acquisition time to the exact month, the lack of announcements regarding future acquisitions, and the absence of information on the classification categories and methods used to classify them. In addition, in many cases, accessing the data itself is difficult, as point clouds are still not freely available in several European states. Furthermore, although ALS data have been collected over multiple periods in some areas of Europe (Table 2), only the point clouds from the most recent period are easily accessible. Hence, it is important to adhere to the FAIR guiding principles for scientific data management and stewardship, which emphasize findability, accessibility, interoperability, and reusability (Wilkinson et al. 2016).

At the moment, only a few European countries provide ALS-derived metrics of vegetation structure in a raster format (e.g., Assmann et al. 2022; Kissling et al. 2023; Külling et al. 2024; Shi and Kissling 2024). However, the choice of vegetation metrics, the methods used to calculate them, and their resolution can vary significantly (Moudrý et al. 2023; Kissling and Shi 2023; Wang et al. 2024). Therefore, it is important to coordinate these efforts from the outset to enable their harmonization and the development of a Europe-wide product. This is particularly relevant to some of the objectives set by the European Commission in the new EU Forestry Strategy 2030, such as monitoring old-growth forests using remote sensing. Such standardization would ensure consistent interpretation and utilization of data across various studies and applications, and improve the reliability and reproducibility of results, enabling comparable assessments of vegetation characteristics.

Access to funding will be a crucial factor in this effort. A European funding initiative similar to 3DEP, led by the EU, would be a good approach to generate vegetation structure metrics from existing data and to collect data in European countries where ALS data is not yet available or where only limited coverage exists, such as the Balkans, Hungary, and Moldova. The first step may lie in creating a continental CHM, which would require consideration of the following aspects of lidar point clouds that present challenges to achieving consistent and reliable products: (i) inconsistencies in pulse density and classification accuracy across datasets/countries, and (ii) temporal inconsistency (e.g., scans with differences in acquisitions in the order of several years or scans conducted in leaf-on vs leaf-off periods).

Combining lidar data from different instruments is challenging, as vegetation structural metrics can differ due to the variations in acquisition parameters, such as point density (Roussel et al. 2017; Zhang et al. 2024, Fischer et al. 2024). Furthermore, point densities may considerably differ depending on when the data were collected (i.e., due to considerable differences in pulse repetition frequencies of current and older scanning instruments) and whether the focus of data acquisition was primarily on terrain or also on vegetation (i.e., winter vs summer acquisition) and infrastructure (e.g., buildings, power lines). However, such inconsistencies can be compensated for by selecting a reasonable resolution of the final product and accounting for temporal differences through consistent metadata. The typical point densities of lidar point clouds available in Europe are around 1-5 points per square meter; still, they vary considerably across the continent (Table 2). For the low point densities, it is advisable to calculate vegetation metrics at coarser resolutions (e.g., 20 meters) to minimize potential errors in estimating the vegetation structure (Ruiz et al. 2014; Wilkes et al. 2015; D'Amico et al. 2021). On the other hand, vegetation metrics, such as upper percentiles of height, are generally less sensitive to point cloud properties (Roussel et al. 2017; LaRue et al. 2022; Fischer et al. 2024), and deriving a canopy height model at a 10-meter resolution should provide a reasonable balance between spatial resolution and vertical accuracy. The point cloud classification across countries, with differences in methods such as automated classification, visual inspection, and AI algorithms, constitute another factor. While classes like terrain, vegetation, and buildings are commonly classified, power lines, bridges, and viaducts are rarely included, potentially introducing bias in vegetation metrics (Shi and Kissling 2023). However, this may not be a major issue if the focus is primarily on forests, where even less accurate classifications can still provide better results than predicted CHMs.

Lastly, the temporal inconsistency of ALS data acquisition across countries is a concern, as ALS surveys remain costly and infrequent. This can limit the usability and accuracy of harmonized vegetation structure maps. Furthermore, ALS data collection often predominantly aims to provide accurate topographic modeling, so many countries carry out scans under leaf-off conditions (such as Slovenia). However, in some countries, scanning is explicitly timed to occur close to peak vegetation greenness (such as France), while in other countries, it depends on the region (e.g., Spain). Some countries may even merge point clouds across different scanning periods. If not accounted for, the resulting differences in phenology (leaf-off vs. leaf-on scanning) could introduce substantial bias into ALS-derived canopy metrics. In addition, as new advancements in scanning technology emerge (e.g., higher pulse repetition frequency, use of multiple wavelengths), older datasets can become less compatible with current data, making it challenging to ensure compatibility. If we consider European countries where data have already been collected or are in the process of being collected, the time span between the first and last scans amounts to about 15 years (2009-2024; Table 2). While this is not optimal, a 10-year difference introduces (as illustrated above) significantly less uncertainty than the predicted maps (Figure 2). It also indicates that with a coordinated effort, it should be possible to achieve a better temporal range similar to the US 3DEP (9 years) for the entire continent of Europe within this decade.

Table 2. Airborne laser scanning campaigns conducted by governmental institutions in Europe.

Country	Number of coverages	Density points/m2	Years of acquisition
Austria (Burgenland)	1	unknown	2019
Austria (Carinthia)	1+	4-8	2006-2015; 2022-ongoing
Austria (Lower Austria)	1	unknown	2011-2022
Austria (Upper Austria)	3	1; 4; 8	2003-2011; 2012-2020; 2021-ongoing
Austria (Salzburg)	2	1; 4-16	2006-2013; 2016-2023
Austria (Styria)	1+	2-4	2008-2014; 2022-ongoing
Austria (Tyrol)	2	0.25-4 (first scan)	2005-2010; 2017-2023
Austria (Vorarlberg)	4	1 (first scan)	2002-2004; 2011; 2017; 2023
Austria (Vienna)	1+	15-20	2007; ongoing updates
Belgium (Brussels)	2	30; 67	2012; 2021
Belgium (Flanders)	2	0.25; 16	2001-2004; 2013-2015
Belgium (Wallonia)	2	0.8; 7	2013-2015; 2021-2022
Czechia	1	1	2009-2013
Denmark	3	0.5; 4-5; 8-10	2007, 2014-15, 2018-23
England	1	2-4	2017-2023
Estonia	3+	0.5 (2008-2015); 2 (18 urban areas)	2008-2011; 2012-2015; 2017-2020; 2021-ongoing
Finland	2	0.5; 5	2008-2019; 2020-25
France	0+	10	2021-2026
Germany (Baden-Württemberg)	2+	0.8; 8; 8	2000-2005; 2016-2022; 2022-ongoing
Germany (Bavaria)	1	4	2013-2024
Germany (Berlin)	1	9.8	2021
Germany (Brandenburg)	1+	1; 5	2008-2012; 2017-ongoing
Germany (Bremen)	1	7	2012-2017
Germany (Hamburg)	3	15-30	2010; 2020; 2022
Germany (Hessen)	2+	4	2007-2014; 2015-2021; 2022-ongoing
Germany (Lower Saxony)	1	4	2014 -2022
Germany (Mecklenburg-Vorpommern)	1	5	2016-2023
Germany (North Rhine Westphalia)	1	4-10	2018-2023
Germany (Rhineland Palatinate)	1+	4	2018-2023
Germany (Saarland)	1	8	2015-2016
Germany (Saxony)	2+	1-5; 5-19; 12-18	2005-2012; 2015-2020; 2020-ongoing
Germany (Saxony-Anhalt)	0+	3-5	2015-ongoing
Germany (Schleswig Holstein)	1	3-4	2005-2007

Germany (Thuringia)	3+	0.05-1.8; 4 (since 2010)	1996-2006; 2010-2013; 2014-2019; 2020-ongoing
Ireland	0+	various	small areas since 2006
Italy	0+	0.4-6	2004-2017
Latvia	1	4	2013-2019
Lichtenstein	2+	minimum of 5 (15-20)	2000-2007*; 2017-2023; 2024-2029
Lithuania	2	6.5	2009-2010; 2019-2022
Luxembourg	2	15	2017; 2019
Malta	2	4; 40	2012; 2018
Netherlands	4+	at least 8-10 since second acquisition	1997-2004; 2007-2012; 2014-2019; 2020-2022; 2023-2025
Northern Ireland	0+	16	2022-ongoing
Norway	1	0.5-5	2009-2018
Poland	1	4-12	2010-2019
Portugal	0+	10	Planed between 2023-2024
Romania	0+	2-8	2004-2025
Scotland	0+	1-2	2011-2022
Slovakia	1+	≥ 15	2017-2022; 2022-2034 (ongoing)
Slovenia	1	2-10	2011, 2014-2015; 2023-ongoing
Spain	2+	0.5-2; 0.5-4; 5	2009-2015; 2015-2022; 2022-25
Sweden	1+	0.25-1; 1-2	2009 - 2017; 2018 - 2024 (ongoing)
Switzerland	2+	minimum of 5 (15-20)	2000-2007; 2017-2023; 2024-2029
Wales	1	2-4	2020-2024

Note that the table is incomplete both in terms of available data and their metadata, as these are documented to varying degrees and reliability. In addition, the years of acquisition may also include the preparation and processing time (i.e., +/- 1 year), as it is often difficult to distinguish whether only the acquisition years are reported or if they also include data processing. Similarly, it is difficult to distinguish whether point or pulse density is reported. Therefore, we use the single term point density.

5. Conclusions

The availability of remote sensing data greatly facilitates ecological research. On the other hand, the growing number of datasets of varying quality introduces challenges regarding which datasets to choose. Users typically do not have the chance (and/or expertise) to critically evaluate the available data. It is, therefore, essential to ensure that data producers clearly communicate the limitations of their datasets. Furthermore, the remote sensing community must ensure the availability of the most appropriate data for ecology, forestry and climate change research. For vegetation structure, harmonized continental products derived from ALS data are the key. The main challenges in developing such products lie in limited spatial and temporal coverage, inconsistencies in point densities, and, to some degree, the accuracy of classification methods. Therefore, to ensure the effective use of ALS in vegetation mapping across Europe, establishing a common data collection protocol to regulate mapping activities (e.g., time of acquisition, pulse densities, updating period) as well as metadata reporting is needed. Besides, studies should focus on developing standardized processing pipelines to account for differences in ALS point clouds, as well as on creating methods for data fusion that leverage both space-borne and ALS data to enhance vegetation monitoring. We strongly recommend that ALS-rich regions such as Europe and the United States prioritize the production of ALS-based canopy height maps over relying solely on modeled global data. In addition, such harmonized data will provide a benchmark for calibrating space-borne laser altimetry products. The improved harmonization will result in better ecosystem monitoring, climate change modeling, and forest management on both continental and global scales.

Acknowledgments

Funded by the European Union. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. This work was funded by the Horizon Europe project EarthBridge (grant agreement no. 101079310). ES was supported by the Internal Grant Agency of the Faculty of Environmental Sciences, Czech University of Life Sciences Prague (2023B0046). TJ and FJF were supported through a Research Project Grant from the Leverhulme Trust (RPG-2020-341). FJF acknowledges support from the European Research Council under the European Union’s Horizon 2020 research and innovation program (Grant Agreement 101001905, FORWARD). PK was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation – 459717468). ŽK was financially supported by the Slovenian Research and Innovation Agency core funding Earth observation and geoinformatics (P2-0406). RR, AC and SR were supported by the DFG under Germany’s Excellence Strategy – EXC 2070 – 390732324. Researcher JAMV conducts his research under the Marie Skłodowska-Curie Actions - COFUND project, which is co-funded by the European Union (MERIT - Grant Agreement No. 101081195). MG was financially supported within the grant APVV-22-0024 of the Slovak Research and Development Agency. GVL acknowledges the PNRR, Missione 4, Componente 2, Avviso 3264/2021, IR0000032—ITINERIS—Italian Integrated Environmental Research

Infrastructures System CUP: B53C22002150006. We are grateful to Ada Perello for providing information on laser scanning campaigns in several European countries.

Author Contributions Statement

VM, RR, MF, MT, GVL, and VB conceived the ideas; VM and ES analysed the data; VM led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data accessibility

The evaluated global canopy height models, that is, the global forest canopy height (Potapov et al., 2021), the high-resolution canopy height model of the Earth (Lang et al., 2023), and the global map of tree canopy height (Tolan et al., 2024) are provided under Creative Commons Attribution 4.0 International License. The canopy height model of Europe at 3 m resolution was kindly provided by Liu et al. (2023). The canopy height models of Giant Mountains National park (2012 and 2022), derived from airborne laser scanning and used for evaluation of global canopy height models, are available from Zenodo: https://doi.org/10.5281/zenodo.14270020.

References

Abshire, J. B., Sun, X., Riris, H., Sirota, J. M., McGarry, J. F., Palm, S., ... & Liiva, P. (2005). Geoscience laser altimeter system (GLAS) on the ICESat mission: on-orbit measurement performance. *Geophysical research letters*, *32*(21).

Alvites, C., O'Sullivan, H., Saverio, F., Marco, M., Santopuoli, G., Chirici, G., ... & Bazzato, E. (2024). Canopy Height Mapper: a Google Earth Engine application for predicting global canopy heights combining GEDI with multi-source data. Environmental Modelling & Software, 106268.

Anderle, M., Brambilla, M., Hilpold, A., Matabishi, J. G., Paniccia, C., Rocchini, D., ... & Seeber, J. (2023). Habitat heterogeneity promotes bird diversity in agricultural landscapes: Insights from remote sensing data. *Basic and Applied Ecology*, *70*, 38-49.

Assmann, J. J., Moeslund, J. E., Treier, U. A., & Normand, S. (2022). EcoDes-DK15: High-resolution ecological descriptors of vegetation and terrain derived from Denmark's national airborne laser scanning data set. *Earth System Science Data*, *14*(2), 823-844.

Atkins, J. W., Fahey, R. T., Hardiman, B. S., & Gough, C. M. (2018). Forest canopy structural complexity and light absorption relationships at the subcontinental scale. *Journal of Geophysical Research: Biogeosciences*, *123*(4), 1387-1405.

Bergen, K. M., Goetz, S. J., Dubayah, R. O., Henebry, G. M., Hunsaker, C. T., Imhoff, M. L., ... & Radeloff, V. C. (2009). Remote sensing of vegetation 3-D structure for biodiversity and habitat: Review and implications for lidar and radar spaceborne missions. *Journal of Geophysical Research: Biogeosciences*, *114*(G2).

Bolton, D. K., Coops, N. C., & Wulder, M. A. (2013). Investigating the agreement between global canopy height maps and airborne Lidar derived height estimates over Canada. *Canadian Journal of Remote Sensing*, *39*(sup1), S139-S151.

Brodie, J. F., Mohd-Azlan, J., Chen, C., Wearn, O. R., Deith, M. C., Ball, J. G., ... & Luskin, M. S. (2023). Landscape-scale benefits of protected areas for tropical biodiversity. *Nature*, *620*(7975), 807-812.

Burns, P., C. Hakkenberg, and S.J. Goetz. 2024. Gridded GEDI Vegetation Structure Metrics and Biomass Density at Multiple Resolutions. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/2339

Cazzolla Gatti, R., Di Paola, A., Bombelli, A., Noce, S., & Valentini, R. (2017). Exploring the relationship between canopy height and terrestrial plant diversity. Plant Ecology, 218, 899-908.

Ceccherini, G., Girardello, M., Beck, P. S., Migliavacca, M., Duveiller, G., Dubois, G., ... & Cescatti, A. (2023). Spaceborne LiDAR reveals the effectiveness of European Protected Areas in conserving forest height and vertical structure. *Communications Earth & Environment*, *4*(1), 97.

Coverdale, T. C., & Davies, A. B. (2023). Unravelling the relationship between plant diversity and vegetation structural complexity: A review and theoretical framework. *Journal of Ecology*, *111*(7), 1378-1395.

D'Amico, G., Vangi, E., Francini, S., Giannetti, F., Nicolaci, A., Travaglini, D., ... & Chirici, G. (2021). Are we ready for a National Forest Information System? State of the art of forest maps and airborne laser scanning data availability in Italy. *IForest*, *14*, 144-154.

Davison, C. W., Assmann, J. J., Normand, S., Rahbek, C., & Morueta-Holme, N. (2023). Vegetation structure from LiDAR explains the local richness of birds across Denmark. *Journal of Animal Ecology*, *92*(7), 1332-1344.

Davies, A. B., & Asner, G. P. (2014). Advances in animal ecology from 3D-LiDAR ecosystem mapping. *Trends in ecology & evolution*, *29*(12), 681-691.

Diaz-Kloch, N., & Murray, D. L. (2024). Harmonizing GEDI and LVIS Data for Accurate and Large-Scale Mapping of Foliage Height Diversity. *Canadian Journal of Remote Sensing*, *50*(1), 2341762.

Dubayah, R., Blair, J. B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., ... & Silva, C. (2020). The Global Ecosystem Dynamics Investigation: High-resolution laser ranging of the Earth's forests and topography. *Science of remote sensing*, *1*, 100002.

Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., ... & Williams, M. (2019). The importance of consistent global forest aboveground biomass product validation. *Surveys in geophysics*, *40*, 979-999.

Fischer, F. J., Jackson, T., Vincent, G., & Jucker, T. (2024). Robust characterisation of forest structure from airborne laser scanning—A systematic assessment and sample workflow for ecologists. *Methods in Ecology and Evolution*.

GEO BON (2022). A Global Biodiversity Observing System to meet the monitoring needs of the Global Biodiversity Framework. Available from https://geobon.org/science-briefs/

Guerra-Hernández, J., & Pascual, A. (2021). Using GEDI lidar data and airborne laser scanning to assess height growth dynamics in fast-growing species: a showcase in Spain. *Forest Ecosystems*, *8*, 1-17.

Hakkenberg, C. R., Tang, H., Burns, P., & Goetz, S. J. (2023). Canopy structure from space using GEDI lidar. *Frontiers in Ecology & the Environment*, *21*(1).

Hancock, S., McGrath, C., Lowe, C., Davenport, I., & Woodhouse, I. (2021). Requirements for a global lidar system: spaceborne lidar with wall-to-wall coverage. *Royal Society open science*, *8*(12), 211166.

Hayashi, M., Saigusa, N., Oguma, H., & Yamagata, Y. (2013). Forest canopy height estimation using ICESat/GLAS data and error factor analysis in Hokkaido, Japan. *ISPRS Journal of Photogrammetry and Remote Sensing*, *81*, 12-18.

Herold, M., Carter, S., Avitabile, V., Espejo, A. B., Jonckheere, I., Lucas, R., ... & De Sy, V. (2019). The role and need for space-based forest biomass-related measurements in environmental management and policy. *Surveys in Geophysics*, *40*, 757-778.

Holcomb, A., Burns, P., Keshav, S., & Coomes, D. A. (2024). Repeat GEDI footprints measure the effects of tropical forest disturbances. *Remote Sensing of Environment*, *308*, 114174.

Jucker, T., Gosper, C. R., Wiehl, G., Yeoh, P. B., Raisbeck-Brown, N., Fischer, F. J., ... & Prober, S. M. (2023). Using multi-platform LiDAR to guide the conservation of the world's largest temperate woodland. *Remote Sensing of Environment*, *296*, 113745.

Jutras-Perreault, M. C., Gobakken, T., Næsset, E., & Ørka, H. O. (2023). Detecting the presence of natural forests using airborne laser scanning data. Forest Ecosystems, 10, 100146.

Kacic, P., Hirner, A., & Da Ponte, E. (2021). Fusing Sentinel-1 and-2 to model GEDI-derived vegetation structure characteristics in GEE for the Paraguayan Chaco. *Remote Sensing*, *13*(24), 5105.

Kacic, P., Thonfeld, F., Gessner, U., & Kuenzer, C. (2023). Forest structure characterization in Germany: novel products and analysis based on GEDI, sentinel-1 and sentinel-2 data. *Remote Sensing*, *15*(8), 1969.

Kakoulaki, G., Martinez, A., & Florio, P. (2021). Non-commercial light detection and ranging (lidar) data in europe. *Publications Office of the European Union: Luxemburg*.

Kemppinen, J., Lembrechts, J. J., Van Meerbeek, K., Carnicer, J., Chardon, N. I., Kardol, P., ... & De Frenne, P. (2024). Microclimate, an important part of ecology and biogeography. *Global Ecology and Biogeography*, *33*(6), e13834.

Khosravipour, A., Skidmore, A. K., Isenburg, M., Wang, T., & Hussin, Y. A. (2014). Generating pit-free canopy height models from airborne lidar. *Photogrammetric Engineering & Remote Sensing*, *80*(9), 863-872.

Kissling, W. D., Shi, Y., Koma, Z., Meijer, C., Ku, O., Nattino, F., ... & Grootes, M. W. (2023). Country-wide data of ecosystem structure from the third Dutch airborne laser scanning survey. *Data in Brief*, *46*, 108798.

Kissling, W. D., & Shi, Y. (2023). Which metrics derived from airborne laser scanning are essential to measure the vertical profile of ecosystems?. *Diversity and Distributions*, *29*(10), 1315-1320.

Külling, N., Adde, A., Fopp, F., Schweiger, A. K., Broennimann, O., Rey, P. L., ... & Guisan, A. (2024). SWECO25: a cross-thematic raster database for ecological research in Switzerland. *Scientific Data*, *11*(1), 21.

Lang, N., Jetz, W., Schindler, K., & Wegner, J. D. (2023). A high-resolution canopy height model of the Earth. *Nature Ecology & Evolution*, *7*(11), 1778-1789.

LaRue, E. A., Fahey, R., Fuson, T. L., Foster, J. R., Matthes, J. H., Krause, K., & Hardiman, B. S. (2022). Evaluating the sensitivity of forest structural diversity characterization to LiDAR point density. *Ecosphere*, *13*(9), e4209.

LaRue, E. A., Knott, J. A., Domke, G. M., Chen, H. Y., Guo, Q., Hisano, M., ... & Fei, S. (2023a). Structural diversity as a reliable and novel predictor for ecosystem productivity. *Frontiers in Ecology and the Environment*, *21*(1), 33-39.

LaRue, E. A., Fahey, R. T., Alveshere, B. C., Atkins, J. W., Bhatt, P., Buma, B., ... & Fei, S. (2023b). A theoretical framework for the ecological role of three-dimensional structural diversity. *Frontiers in Ecology and the Environment*, *21*(1), 4-13.

Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar remote sensing for ecosystem studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. *BioScience*, *52*(1), 19-30.

Lefsky, M. A. (2010). A global forest canopy height map from the Moderate Resolution Imaging Spectroradiometer and the Geoscience Laser Altimeter System. *Geophysical Research Letters*, *37*(15).

Li, W., Duveiller, G., Wieneke, S., Forkel, M., Gentine, P., Reichstein, M., ... & Orth, R. (2024). Regulation of the global carbon and water cycles through vegetation structural and physiological dynamics. *Environmental Research Letters*, *19*(7), 073008.

Liang, M., González-Roglich, M., Roehrdanz, P., Tabor, K., Zvoleff, A., Leitold, V., ... & Duncanson, L. (2023). Assessing protected area's carbon stocks and ecological structure at regional-scale using GEDI lidar. *Global Environmental Change*, *78*, 102621.

Liu, A., Cheng, X., & Chen, Z. (2021). Performance evaluation of GEDI and ICESat-2 laser altimeter data for terrain and canopy height retrievals. *Remote Sensing of Environment*, *264*, 112571.

Liu, S., Brandt, M., Nord-Larsen, T., Chave, J., Reiner, F., Lang, N., ... & Fensholt, R. (2023). The overlooked contribution of trees outside forests to tree cover and woody biomass across Europe. *Science Advances*, *9*(37), eadh4097.

Lowe, C. J., McGrath, C. N., Hancock, S., Davenport, I., Todd, S., Hansen, J., ... & Macdonald, M. (2024). Spacecraft and optics design considerations for a spaceborne lidar mission with spatially continuous global coverage. *Acta Astronautica*, *214*, 809-816.

Mandl, L., Stritih, A., Seidl, R., Ginzler, C., & Senf, C. (2023). Spaceborne LiDAR for characterizing forest structure across scales in the European Alps. *Remote Sensing in Ecology and Conservation*, *9*(5), 599-614.

Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., ... & Zwally, J. (2017). The Ice, Cloud, and land Elevation Satellite-2 (ICESat-2): science requirements, concept, and implementation. *Remote sensing of environment*, *190*, 260-273.

Marselis, S. M., Keil, P., Chase, J. M., & Dubayah, R. (2022). The use of GEDI canopy structure for explaining variation in tree species richness in natural forests. Environmental Research Letters, 17(4), 045003.

Meyer, H., & Pebesma, E. (2022). Machine learning-based global maps of ecological variables and the challenge of assessing them. *Nature Communications*, *13*(1), 2208.

Milenković, M., Reiche, J., Armston, J., Neuenschwander, A., De Keersmaecker, W., Herold, M., & Verbesselt, J. (2022). Assessing Amazon rainforest regrowth with GEDI and ICESat-2 data. *Science of Remote Sensing*, *5*, 100051.

Moudrý, V., Moudrá, L., Barták, V., Bejček, V., Gdulová, K., Hendrychová, M., ... & Šálek, M. (2021). The role of the vegetation structure, primary productivity and senescence derived from airborne LiDAR and hyperspectral data for birds diversity and rarity on a restored site. *Landscape and Urban Planning*, *210*, 104064.

Moudrý, V., Gdulová, K., Gábor, L., Šárovcová, E., Barták, V., Leroy, F., ... & Prošek, J. (2022). Effects of environmental conditions on ICESat-2 terrain and canopy heights retrievals in Central European mountains. *Remote Sensing of Environment*, *279*, 113112.

Moudrý, V., Cord, A. F., Gábor, L., Laurin, G. V., Barták, V., Gdulová, K., ... & Wild, J. (2023). Vegetation structure derived from airborne laser scanning to assess species distribution and habitat suitability: The way forward. *Diversity and Distributions*, *29*(1), 39-50.

Moudrý, V., Gábor, L., Marselis, S., Pracná, P., Barták, V., Prošek, J., ... & Wild, J. (2024a). Comparison of three global canopy height maps and their applicability to biodiversity modeling: Accuracy issues revealed. *Ecosphere*, *15*(10), e70026.

Moudrý, V., Prošek, J., Marselis, S., Marešová, J., Šárovcová, E., Gdulová, K., ... & Wild, J. (2024b). How to Find Accurate Terrain and Canopy Height GEDI Footprints in Temperate Forests and Grasslands?. *Earth and Space Science*, *11*(10), e2024EA003709.

Mulverhill, C., Coops, N. C., Hermosilla, T., White, J. C., & Wulder, M. A. (2022). Evaluating ICESat-2 for monitoring, modeling, and update of large area forest canopy height products. *Remote Sensing of Environment*, *271*, 112919.

Murphy, B. A., May, J. A., Butterworth, B. J., Andresen, C. G., & Desai, A. R. (2022). Unraveling Forest Complexity: Resource Use Efficiency, Disturbance, and the Structure-Function Relationship. *Journal of Geophysical Research: Biogeosciences*, *127*(6), e2021JG006748.

Parra, A., & Simard, M. (2023). Evaluation of Tree-Growth Rate in the Laurentides Wildlife Reserve Using GEDI and Airborne-LiDAR Data. *Remote Sensing*, *15*(22), 5352.

Pascual, A., Tupinambá-Simões, F., & de Conto, T. (2022). Using multi-temporal tree inventory data in eucalypt forestry to benchmark global high-resolution canopy height models. A showcase in Mato Grosso, Brazil. *Ecological Informatics*, *70*, 101748.

Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H., Scholes, R. J., ... & Wegmann, M. (2013). Essential biodiversity variables. *Science*, *339*(6117), 277-278.

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., ... & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, *253*, 112165.

Rosen, A., Jörg Fischer, F., Coomes, D. A., Jackson, T. D., Asner, G. P., & Jucker, T. (2024). Tracking shifts in forest structural complexity through space and time in human-modified tropical landscapes. *Ecography*, e07377.

Roussel, J. R., Caspersen, J., Béland, M., Thomas, S., & Achim, A. (2017). Removing bias from LiDAR-based estimates of canopy height: Accounting for the effects of pulse density and footprint size. *Remote Sensing of Environment*, *198*, 1-16.

Ruiz, L. A., Hermosilla, T., Mauro, F., & Godino, M. (2014). Analysis of the influence of plot size and LiDAR density on forest structure attribute estimates. *Forests*, *5*(5), 936-951.

Ruiz-Jaén, M. C., & Aide, T. M. (2005). Vegetation structure, species diversity, and ecosystem processes as measures of restoration success. *Forest Ecology and Management*, *218*(1-3), 159-173.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T., Salas, W., ... & Morel, A. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the national academy of sciences, 108(24), 9899-9904.

Schutz, B. E., Zwally, H. J., Shuman, C. A., Hancock, D., & DiMarzio, J. P. (2005). Overview of the ICESat mission. *Geophysical research letters*, *32*(21).

Schwartz, M., Ciais, P., De Truchis, A., Chave, J., Ottlé, C., Vega, C., ... & Fayad, I. (2023). FORMS: Forest Multiple Source height, wood volume, and biomass maps in France at 10 to 30 m resolution based on Sentinel-1, Sentinel-2, and Global Ecosystem Dynamics Investigation (GEDI) data with a deep learning approach. *Earth System Science Data*, *15*(11), 4927-4945.

Seidel, D., & Ammer, C. (2023). Towards a causal understanding of the relationship between structural complexity, productivity, and adaptability of forests based on principles of thermodynamics. *Forest Ecology and Management*, *544*, 121238.

Shi, Y., & Kissling, W. D. (2023). Performance, effectiveness and computational efficiency of powerline extraction methods for quantifying ecosystem structure from light detection and ranging. *GIScience & Remote Sensing*, *60*(1), 2260637.

Shi, Y., & Kissling, W. D. (2024). Multi-temporal high-resolution data products of ecosystem structure derived from country-wide airborne laser scanning surveys of the Netherlands. Earth System Science Data Discussions, 2024, 1-44.

Simard, M., Pinto, N., Fisher, J. B., & Baccini, A. (2011). Mapping forest canopy height globally with spaceborne lidar. *Journal of Geophysical Research: Biogeosciences*, *116*(G4).

Skidmore, A. K., Coops, N. C., Neinavaz, E., Ali, A., Schaepman, M. E., Paganini, M., ... & Wingate, V. (2021). Priority list of biodiversity metrics to observe from space. *Nature ecology & evolution*, *5*(7), 896-906.

Smith, A. B., Vogeler, J. C., Bjornlie, N. L., Squires, J. R., Swayze, N. C., & Holbrook, J. D. (2022). Spaceborne LiDAR and animal-environment relationships: An assessment for forest carnivores and their prey in the Greater Yellowstone Ecosystem. *Forest Ecology and Management*, *520*, 120343.

Stein, A., Gerstner, K., & Kreft, H. (2014). Environmental heterogeneity as a universal driver of species richness across taxa, biomes and spatial scales. *Ecology letters*, *17*(7), 866-880.

Stoker, J. M. (2020). *Defining technology operational readiness for the 3D Elevation Program—A plan for investment, incubation, and adoption* (No. 2020-1015). US Geological Survey.

Stoker, J., & Miller, B. (2022). The accuracy and consistency of 3d elevation program data: A systematic analysis. *Remote Sensing*, *14*(4), 940.

Stritih, A., Seidl, R., & Senf, C. (2023). Alternative states in the structure of mountain forests across the Alps and the role of disturbance and recovery. *Landscape Ecology*, *38*(4), 933-947.

Tang, H., Stoker, J., Luthcke, S., Armston, J., Lee, K., Blair, B., & Hofton, M. (2023). Evaluating and mitigating the impact of systematic geolocation error on canopy height measurement performance of GEDI. *Remote Sensing of Environment*, *291*, 113571.

Tews, J., Brose, U., Grimm, V., Tielbörger, K., Wichmann, M. C., Schwager, M., & Jeltsch, F. (2004). Animal species diversity driven by habitat heterogeneity/diversity: the importance of keystone structures. *Journal of biogeography*, *31*(1), 79-92.

Tolan, J., Yang, H. I., Nosarzewski, B., Couairon, G., Vo, H. V., Brandt, J., ... & Couprie, C. (2024). Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. *Remote Sensing of Environment*, *300*, 113888.

Torresani, M., Rocchini, D., Sonnenschein, R., Zebisch, M., Hauffe, H. C., Heym, M., ... & Tonon, G. (2020). Height variation hypothesis: A new approach for estimating forest species diversity with CHM LiDAR data. Ecological Indicators, 117, 106520.

United Nations et al. (2021). System of Environmental-Economic Accounting—Ecosystem Accounting (SEEA EA). White cover publication, pre-edited text subject to official editing. Available at: https://seea.un.org/ecosystem-accounting.

United Nations (2022). Guidelines on Biophysical Modelling for Ecosystem Accounting. United Nations Department of Economic and Social Affairs, Statistics Division, New York

Valbuena, R., O'Connor, B., Zellweger, F., Simonson, W., Vihervaara, P., Maltamo, M., ... & Coops, N. C. (2020). Standardizing ecosystem morphological traits from 3D information sources. *Trends in Ecology & Evolution*, *35*(8), 656-667.

Vogeler, J. C., Fekety, P. A., Elliott, L., Swayze, N. C., Filippelli, S. K., Barry, B., ... & Vierling, K. T. (2023). Evaluating GEDI data fusions for continuous characterizations of forest wildlife habitat. *Frontiers in Remote Sensing*, *4*, 1196554.

Wang, J., Choi, D. H., LaRue, E., Atkins, J. W., Foster, J. R., Matthes, J. H., ... & Hardiman, B. S. (2024). NEON-SD: A 30-m Structural Diversity Product Derived from the NEON Discrete-Return LiDAR Point Cloud. Scientific Data, 11(1), 1174.

Wildermuth, B., Dönges, C., Matevski, D., Penanhoat, A., Seifert, C. L., Seidel, D., ... & Schuldt, A. (2023). Tree species identity, canopy structure and prey availability differentially affect canopy spider diversity and trophic composition. *Oecologia*, *203*(1), 37-51.

Wilkes, P., Jones, S. D., Suarez, L., Haywood, A., Woodgate, W., Soto-Berelov, M., ... & Skidmore, A. K. (2015). Understanding the effects of ALS pulse density for metric retrieval across diverse forest types. *Photogrammetric Engineering & Remote Sensing*, *81*(8), 625-635.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., ... & Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. Scientific data, 3(1), 1-9.

Xu, J., Farwell, L., Radeloff, V. C., Luther, D., Songer, M., Cooper, W. J., & Huang, Q. (2024). Avian diversity across guilds in North America versus vegetation structure as measured by the Global Ecosystem Dynamics Investigation (GEDI). Remote Sensing of Environment, 315, 114446.

Zhang, B., Fischer, F. J., Prober, S. M., Yeoh, P. B., Gosper, C. R., Zdunic, K., & Jucker, T. (2024). Robust retrieval of forest canopy structural attributes using multi-platform airborne LiDAR. *Remote Sensing in Ecology and Conservation*.