AGU ADVANCING EARTH AND SPACE SCIENCES

Earth and Space Science

DATA ARTICLE
10.1029/2025EA004544

Special Collection:
Surface Topography and Vegetation: Science, Measurements, and Technologies

Spaceborne Canopy Height Products Should Be Complemented With Airborne Laser Scanning Data: Toward a European Canopy Height Model

Vítězslav Moudrý[1], Ruben Remelgado[2], Matthias Forkel[3], Michele Torresani[4,5], Gaia Vaglio Laurin[6], Eliška Šárovcová[1], Virginia E. Garcia Millan[7], Fabian Jörg Fischer[8,9], Tommaso Jucker[8], Michal Gallay[10], Patrick Kacic[11], Christopher R. Hakkenberg[12], Žiga Kokalj[13], Krzysztof Stereńczak[14], Yousef Erfanifard[15,16], Duccio Rocchini[1,17], Jiří Prošek[1], Stephanie Roilo[2], Kateřina Gdulová[1], Anna F. Cord[2], Michela Perrone[1], Juan Alberto Molina-Valero[1], Jiří Šmída[18], Peter Surový[19], Zlatica Melichová[19], Marco Malavasi[20], Rudolf Urban[21], Martin Štroner[21], Dominik Seidel[22], Szilárd Szabó[23], László Bertalan[23], Anette Eltner[3], Roberto Cazzolla Gatti[17], Ján Kaňuk[10,24], Vojtěch Barták[1], Daniel Franke[1], Benjamin Brede[25], Qian Song[25], Mikhail Urbazaev[25], and W. Daniel Kissling[26]

[1]Department of Spatial Sciences, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Praha, Czech Republic, [2]Agro-Ecological Modeling Group, Institute of Crop Science and Resource Conservation, University of Bonn, Bonn, Germany, [3]Faculty of Environmental Sciences, TUD Dresden University of Technology, Institute of Photogrammetry and Remote Sensing, Dresden, Germany, [4]Faculty of Agricultural, Environmental and Food Sciences, Free University of Bozen/Bolzano, Bolzano, Italy, [5]Competence Centre for Plant Health, Bolzano, Italy, [6]Research Institute on Terrestrial Ecosystems, National Research Council, Montelibretti Research Area, Montelibretti, Italy, [7]Khaos Research, Institute of Software Technology and Engineering (ITIS), University of Malaga, Málaga, Spain, [8]School of Biological Sciences, University of Bristol, Bristol, UK, [9]TUM School of Life Sciences, Ecosystem Dynamics and Forest Management, Technical University of Munich, Freising, Germany, [10]Faculty of Science, Institute of Geography, Pavol Jozef Šafárik University in Košice, Košice, Slovakia, [11]Department of Remote Sensing, University of Würzburg, Institute of Geography and Geology, Würzburg, Germany, [12]Department of Geography, University of California at Los Angeles (UCLA), Los Angeles, CA, USA, [13]Research Centre of the Slovenian Academy of Sciences and Arts, Ljubljana, Slovenia, [14]Department of Geomatics, Forest Research Institute, Sękocin Stary, Poland, [15]Department of Remote Sensing and GIS, College of Geography, University of Tehran, Tehran, Iran, [16]IDEAS NCBR Sp. z o.o., Warsaw, Poland, [17]BIOME Lab, Department of Biological, Geological and Environmental Sciences, Alma Mater Studiorum University of Bologna, Bologna, Italy, [18]Department of Geoinformatics and Didactics of Informatics, Faculty of Science, Humanities and Education, Technical University Liberec, Liberec, Czech Republic, [19]Faculty of forestry and wood science, Czech University of Life Sciences Prague, Praha, Czech Republic, [20]Department of Chemistry, Physics, Mathematics and Natural Sciences, University of Sassari, Sassari, Italy, [21]Department of Special Geodesy, Faculty of Civil Engineering, Czech Technical University in Prague, Prague, Czech Republic, [22]Department for Spatial Structures and Digitization of Forest, Faculty of Forest Sciences and Forest Ecology, Georg August University of Göttingen, Göttingen, Germany, [23]Department of Physical Geography and Geoinformatics, Faculty of Science and Technology, University of Debrecen, Debrecen, Hungary, [24]Photomap, s.r.o, Košice, Slovakia, [25]GFZ Helmholtz Centre for Geosciences, Potsdam, Germany, [26]Institute for Biodiversity and Ecosystem Dynamics (IBED), University of Amsterdam, Amsterdam, The Netherlands

Key Points:

- About 30 European countries now provide nationwide airborne laser scanning, and these data should be prioritized over predicted products
- Existing airborne laser scanning data should be used to derive continental-scale vegetation metrics available in raster format
- Improved transnational coordination is needed to advance vegetation monitoring with airborne laser scanning data in Europe

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

V. Moudrý and R. Remelgado,
moudry@fzp.czu.cz;
rsoaresl@uni-bonn.de

Citation:

Moudrý, V., Remelgado, R., Forkel, M., Torresani, M., Laurin, G. V., Šárovcová, E., et al. (2026). Spaceborne canopy height products should be complemented with airborne laser scanning data: Toward a European canopy height model. *Earth and Space Science*, *13*, e2025EA004544. https://doi.org/10.1029/2025EA004544

Received 15 JUN 2025
Accepted 7 DEC 2025

Author Contributions:

Conceptualization: Vítězslav Moudrý, Ruben Remelgado, Matthias Forkel, Michele Torresani, Gaia Vaglio Laurin, W. Daniel Kissling
Data curation: Vítězslav Moudrý
Formal analysis: Vítězslav Moudrý, Eliška Šárovcová
Funding acquisition: Vítězslav Moudrý

Abstract Measuring and mapping vegetation structure is essential for understanding the functioning of terrestrial ecosystems and for informing environmental policies. Recent years have seen a growing demand for high-resolution data on vegetation structure, driving their prediction at fine resolutions (1–30 m) at state, continental, and global spatial extents by combining satellite data with machine learning. As these initiatives expand, it is crucial to actively discuss the quality and usability of these products. Here, we briefly summarize current efforts to map vegetation structure and show that continental-to-global canopy height models (CHMs) exhibit significant errors in canopy heights compared to national airborne laser scanning (ALS) data. We recommend that regions with abundant ALS data, such as Europe, prioritize using ALS-based canopy height metrics rather than relying on less accurate predictions from satellite products. Despite variations in ALS data characteristics, such as temporal inconsistencies and differences in acquisition characteristics and classification accuracy, the generation of spatially contiguous canopy height products in raster format at fine spatial resolution is necessary and feasible. This requires coordinating efforts for data and survey harmonization, developing standardized processing pipelines and continent-wide ALS products, and ensuring free access for research and environmental policy. We show that ALS data now cover most of Europe, with newer surveys achieving higher

Investigation: Vítězslav Moudrý
Methodology: Vítězslav Moudrý
Project administration: Vítězslav Moudrý
Supervision: Vítězslav Moudrý
Visualization: Vítězslav Moudrý, Jiří Šmída
Writing – original draft: Vítězslav Moudrý
Writing – review & editing: Vítězslav Moudrý, Ruben Remelgado, Matthias Forkel, Michele Torresani, Gaia Vaglio Laurin, Eliška Šárovcová, Virginia E. Garcia Millan, Fabian Jörg Fischer, Tommaso Jucker, Michal Gallay, Patrick Kacic, Christopher R. Hakkenberg, Žiga Kokalj, Krzysztof Stereńczak, Yousef Erfanifard, Duccio Rocchini, Jiří Prošek, Stephanie Roilo, Kateřina Gdulová, Anna F. Cord, Michela Perrone, Juan Alberto Molina-Valero, Jiří Šmída, Peter Surový, Zlatica Melichová, Marco Malavasi, Rudolf Urban, Martin Štroner, Dominik Seidel, Szilárd Szabó, László Bertalan, Anette Eltner, Roberto Cazzolla Gatti, Ján Kaňuk, Vojtěch Barták, Daniel Franke, Benjamin Brede, Qian Song, Mikhail Urbazaev, W. Daniel Kissling

point densities, improving their suitability for vegetation mapping. Beyond numerous applications in forestry, ecology, and conservation, such data sets are crucial for calibrating future Earth Observation missions, making them essential for producing reliable and accurate global, fine-resolution vegetation structure data.

Plain Language Summary Understanding the structure of vegetation is important for studying ecosystems and making informed environmental decisions. To meet the growing need for detailed vegetation data, scientists are combining satellite data with machine learning to estimate vegetation structure at very fine scales. However, these satellite-based models can have large errors when compared to more accurate measurements collected from airborne laser scanning (ALS). In this study, we show that in regions such as Europe, where extensive ALS data are available, it's better to use these local data than to rely on less accurate predictions from satellite products. Currently, around 30 European countries have completed or are close to completing nationwide airborne laser scanning, with several others partially covered. Newer acquisitions are being collected at increasingly higher point densities, providing more detailed information about 3D vegetation structure. We therefore emphasize the need to create consistent and accessible vegetation height maps using ALS data. This will require better coordination of data collection, standardized processing, and open data access. These detailed maps are not only useful for applications in forestry, ecology, and conservation, but they are also essential for improving future satellite missions that monitor Earth's vegetation.

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 monitoring the cover, distribution, and vertical profile of ecosystems (Pereira et al., 2013; Valbuena et al., 2020; Skidmore et al., 2021). Vegetation structure—the horizontal and vertical distribution of vegetation biomass—is one of the key components of ecosystem structure, especially in terrestrial ecosystems. It 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, Knott, et al., 2023; Li et al., 2024). Furthermore, vegetation structure creates unique habitats that support species coexistence across different vegetation layers (Davies & Asner, 2014; Kemppinen et al., 2024; Moudrá et al., 2025; Moudrý et al., 2021; Wildermuth et al., 2023). The prevailing theory is that structurally complex vegetation stands are most effective in optimizing the incoming light and water resources, leading to better carbon assimilation (Atkins et al., 2018; Seidel & Ammer, 2023), and that they provide a large number of ecological niches, thereby enhancing biodiversity (Coverdale & Davies, 2023; LaRue, Fahey, et al., 2023; Stein et al., 2014; Tews et al., 2004; Torresani et al., 2020). Consequently, data on vegetation structure is essential for a global biodiversity observing system (Gonzalez et al., 2023), supports the United Nations' System of Environmental-Economic Accounting (United Nations, 2021, 2022), contributes to the EU Forest Strategy for 2030 (European Commission, 2021), and plays a key role in tracking progress toward global biodiversity targets and Sustainable Development Goals (SDGs) (Skidmore et al., 2021).

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 across a variety of habitats and landscapes, including grasslands (Zlinszky et al., 2014), shrublands (Klouček et al., 2022), wetlands (Koma et al., 2021), forests (Toivonen et al., 2023), agricultural areas (Grondard et al., 2025), urban areas (Caynes et al., 2016), and Natura 2000 sites (Shi et al., 2025), from local to global scales (Herold et al., 2019; Janiec et al., 2025; Jutras-Perreault et al., 2023; Liu et al., 2023; Rosen et al., 2024; Stereńczak et al., 2018; Vaglio Laurin et al., 2025; Valbuena et al., 2020; White et al., 2025). Particularly, LiDAR sensors onboard airplanes (i.e., airborne laser scanning; ALS) have considerable potential to advance national monitoring programs (e.g., Assmann et al., 2022; Kissling et al., 2023). Moreover, robust approaches to convert ALS data into structural metrics are available (Fischer et al., 2019, 2024; Hawryło et al., 2024; Kissling et al., 2024). However, while ALS data provides high spatial resolution, its spatial extent and temporal availability are limited (e.g., Moudrý et al., 2023; Okyay et al., 2019). Access costs for end users of ALS have decreased in recent years, especially where national programmes or mapping agencies release data openly, but large-scale continuous coverage exists only in a few regions, mostly in Europe, North America, and Australia, with several other countries, such as New Zealand and Japan. A few countries (e.g., Denmark, Estonia, Netherlands, or Spain) have even mapped their entire territory more than once.

Recent advances in spaceborne LiDAR missions, such as the Global Ecosystem Dynamics Investigation (GEDI) and the Ice, Cloud, and land Elevation Satellite-2 (ICESat-2), can help to address the limited spatial and temporal extent of ALS data (Dubayah et al., 2020; Markus et al., 2017). These missions provide free data that have enabled the creation of global models of vegetation structure (e.g., Burns et al., 2024; Mulverhill et al., 2022), supporting innovative and impactful research. For instance, vegetation structure products derived from spaceborne LiDAR data have been used to monitor forest and woodland structure and regrowth (Jucker et al., 2023; Milenković et al., 2022; 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 (Brodie et al., 2023; Ceccherini et al., 2023; Lang et al., 2023; Liang et al., 2023), and assess species diversity and species-environment relationships (Marselis et al., 2022; Smith et al., 2022; Vogeler et al., 2023; Xu et al., 2024). However, the spatial coverage of spaceborne LiDAR measurements is sparse and discrete, and their derived products, such as global canopy height models (CHMs), have a low spatial resolution (Burns et al., 2024) or suffer from accuracy issues (Mandl et al., 2023; Moudrý, Gábor, et al., 2024), which constrain their applicability (Hakkenberg et al., 2023).

Here, we aim to highlight the potential of ALS data to complement spaceborne LiDAR products. In particular, we (a) provide a brief overview of spaceborne LiDAR missions that measure vegetation structure, (b) examine the accuracy of CHMs predicted from these missions, (c) highlight recent developments in potential mapping of the Earth's surface integrating airborne and satellite data, and (d) propose a broader use of ALS data, emphasizing the need to develop continental (e.g., Europe-wide) CHMs. We identify the challenges involved and offer general recommendations for future progress.

2. Measuring Vegetation Structure With Spaceborne 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, spaceborne LiDAR is 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 vegetation structure in response to global monitoring requirements, with LiDAR playing an important role (Skidmore et al., 2021). The first global data set 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). That mission was primarily intended for measuring polar ice caps, but it also enabled the development of data sets for ground elevation and canopy height (Schutz et al., 2005; Simard et al., 2011). In 2018, NASA launched two spaceborne LiDAR missions, ICESat-2 (Magruder et al., 2021; Markus et al., 2017) and GEDI (Dubayah et al., 2020), aimed at providing near-global data on terrain and canopy height, among other objectives. Yet, technical challenges related to spatial and temporal coverage as well as data accuracy persist (Fernandez-Diaz et al., 2022; Hancock et al., 2012, 2021; Liu et al., 2021; Pang et al., 2022; Velikova et al., 2024).

Although current spaceborne LiDAR missions have substantially higher sampling densities than their predecessors, the derived products still have limited spatial and temporal coverage. A major limitation of spaceborne LiDAR sensors is that they collect discrete data samples along narrow orbital tracks (transects) rather than producing continuous, wall-to-wall coverage. This sampling design means that spaceborne LiDAR observations represent only a small fraction of the Earth's surface, leaving large gaps between ground tracks and individual footprints. As a result, these sensors cannot directly capture spatially contiguous patterns of vegetation structure. Notably, for some applications, such as in forestry, transect-based (profiling) LiDAR data are sufficient to characterize forest conditions over large regions in a timely and cost-effective manner, though their use has been increasingly overshadowed by scanning LiDAR instruments (see review by Wulder et al., 2012). In contrast, applications such as ecosystem (habitat) mapping and ecosystem extent accounting, assessing habitat fragmentation, or species-environment relationship analyses require spatially continuous data sets to capture fine-scale patterns across the landscape. For example, within agricultural landscapes, structural complexity is often provided by isolated trees and linear features such as hedgerows and tree belts, which serve as important habitats contributing to biodiversity and carbon storage (Grondard et al., 2025; Liu et al., 2023). Similarly, urban vegetation is recognized for its multiple ecological and societal benefits, such as mitigating the urban heat island effect, improving air quality, and sequestering carbon, making detailed monitoring of tree attributes essential (Dong, Tang, et al., 2025; Tang et al., 2024). However, spaceborne LiDAR data remain insufficient for producing high-resolution, continuous vegetation structure data for such purposes.

GEDI was expected to sample only 4% of the Earth's land surface over a 2-year mission, enabling the generation of near-global gridded vegetation structure metrics from aggregated GEDI waveforms, including canopy height and structural diversity at three spatial resolutions: 1, 6, and 12 km (Burns et al., 2024). Similarly, the ICESat-2 mission is designed to generate a global canopy height product at a 1-km resolution (Guenther et al., 2024). However, in Europe, the sampling intensity of ICESat-2 is even lower than that of GEDI due to its orbital configuration (Markus et al., 2017). Furthermore, GEDI and ICESat-2 missions are not designed to acquire laser pulses over the same location twice (i.e., they cannot provide direct observations of vegetation change (but see Clark et al., 2025; Holcomb et al., 2024; Liu et al., 2025)). In addition, 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, Prošek, et al., 2024; Moudrý et al., 2022; Pardini et al., 2019). Indeed, the operational use of GEDI and ICESat-2 data remains limited, as canopy height accuracy falls short of the thresholds typically required for environmental and forestry applications (approx. 2 m; Bergen et al., 2009; Fassnacht et al., 2025), and sampling density and coverage are strongly shaped by the trade-offs between observation accuracy and required spatial resolution of derived products (Pracná et al., 2025). Moreover, GEDI observations are limited to latitudes between approximately −52° and 52°, excluding higher-latitude regions (Dubayah et al., 2020). This means that large parts of Europe are not covered by GEDI observations, which, in turn, restricts the usability of the data for continent-wide studies. A near global-scale 1 km resolution CHM is a significant achievement but has limited utility for applications such as ecosystem mapping or species-environment relationship assessments, which typically require finer spatial resolution (Anderle et al., 2023; Davison et al., 2023; Smith et al., 2022; Vogeler et al., 2023). Development of fine-resolution continuous data sets so far relies on interpolation or data fusion with other remote sensing products (e.g., optical or radar imagery), which is associated with known limitations of the resulting models (Section 3). Although future advances are expected to significantly enhance accuracy and resolution (Section 4), alternative solutions must also be explored to meet immediate monitoring needs (Section 5).

3. Spatially Contiguous, High-Resolution CHMs, and Their Limitations

The lack of global high-resolution data on vertical vegetation structure has stimulated the use of spaceborne LiDAR data in combination with other satellite products to make spatially contiguous predictions of vegetation structure (see review by Coops et al., 2021), such as canopy height, total canopy cover, above-ground biomass density, and foliage height diversity at fine resolutions, such as 10 m or 30 m (e.g., Diaz-Kloch & Murray, 2024; Kacic et al., 2021, 2023; Schwartz et al., 2023). A common approach to producing high-resolution, wall-to-wall data on vegetation structure lies in training predictive models that combine direct but discrete height measurements (e.g., from spaceborne LiDAR ICESat, GEDI, or ICESat-2) with spatially contiguous data (e.g., from spaceborne optical and radar data). The model establishes a relationship between the discrete and the continuous data that enables the estimation of canopy height at locations not directly measured by LiDAR (Bergen et al., 2009; Lefsky, 2010). Predicted CHMs are among the most common high-resolution vegetation structure products available at continental (Liu et al., 2023; Turubanova et al., 2023) and global scales (Lang et al., 2023; Pauls et al., 2024; Potapov et al., 2021; Weber et al., 2025), making them suitable for illustrating the pros and cons of such data. Recently, a web application for predicting canopy height, which combines GEDI with other remote sensing data, has been developed, making this approach easily accessible (Alvites et al., 2025).

Several continental or global predicted CHMs have been produced. The first such data set 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 and 10 m spatial resolutions, respectively. Instead of deriving training canopy heights from satellite LiDARs, models can also be calibrated using ALS data, which, when combined with very high-resolution (VHR) satellite imagery, enables predictions at substantially finer spatial resolutions (e.g., Liu et al., 2023; Wagner et al., 2025). For example, Liu

Table 1
Predicted Global (Continental) Canopy Height Models (CHMs) Evaluated in This Study

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	Meta and World Resource Institute; Tolan et al. (2024)	1 m	4.4 m	2018–2020

Note. The root mean square error (RMSE) value reported by the authors of individual CHMs in the original publications is presented here.

et al. (2023) used canopy height from ALS data and PlanetScope imagery to predict canopy heights in Europe at a resolution of 3 m. Likewise, 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 spaceborne 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 researchers to store and handle (Kissling et al., 2022; Kissling & Shi, 2023; Moudrý et al., 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 data sets is questionable (Duncanson et al., 2019; Meyer & Pebesma, 2022). Modeling canopy height is a complex process that involves errors and biases from multiple sources, ranging from ground detection with spaceborne LiDAR to the saturation of optical data in closed-canopy forests (e.g., Réjou-Méchain et al., 2019). 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, Gábor, et al., 2024).

3.1. Validation of Predicted Global CHMs' Accuracies

To demonstrate the limitations of predicted CHMs, we followed a recent study by Moudrý, Gábor, et al. (2024), who compared three global predicted CHMs. In addition to their evaluation, we added a continental canopy height map for Europe produced by Liu et al. (2023) and a ten-year-old ALS scan, which allowed us to assess whether the accuracy of the predicted CHMs is higher than that of the outdated ALS data. We used a 2022 ALS scan from the Giant Mountains National Park (Czechia) as a reference and compared it to four recent satellite-derived predicted CHMs (Table 1) as well as to another ALS scan acquired 10 years earlier (i.e., 2012; all ALS data were processed with standard methods, cf. Moudrý, Gábor, et al., 2024).

The study area was selected because it provides both a representative example of European landscape heterogeneity and access to high-quality ALS data collected at multiple time points. The Giant Mountains National Park can be regarded as broadly representative of many European landscapes, as it encompasses a mosaic of natural and human-modified ecosystems. These cover a diverse, rugged landscape shaped by glacial and postglacial processes and a broad altitudinal gradient (approximately 400–1,600 m a.s.l.). Canopy height of forest stands is typically up to 35 m, with some mature patches reaching up to 45 m. Vegetation transitions from lowland managed forests and extensive spruce (Picea abies) monocultures to montane and subalpine zones with thickets of dwarf pine (Pinus mugo), alpine meadows, and sparsely vegetated rocky areas. The park also includes peat bogs and remnants of native deciduous and mixed forests dominated by beech (Fagus sylvatica). This heterogeneous mosaic of open areas with low vegetation, interspersed with forested patches of varying canopy height (Figures 1 and 2) mirrors ecological and structural variability found across much of Central and Western Europe, with the exception of extensive flat coastal regions, such as in the Netherlands or northern Germany. Therefore, although regionally specific, the Giant Mountains landscape represents a realistic and data-rich test environment for evaluating CHMs.

The evaluation demonstrated that current global and continental CHMs exhibit limited accuracy in our study area, with RMSEs ranging from 6.4 to 11.7 m (Figures 1 and 2). This is consistent with several recent independent

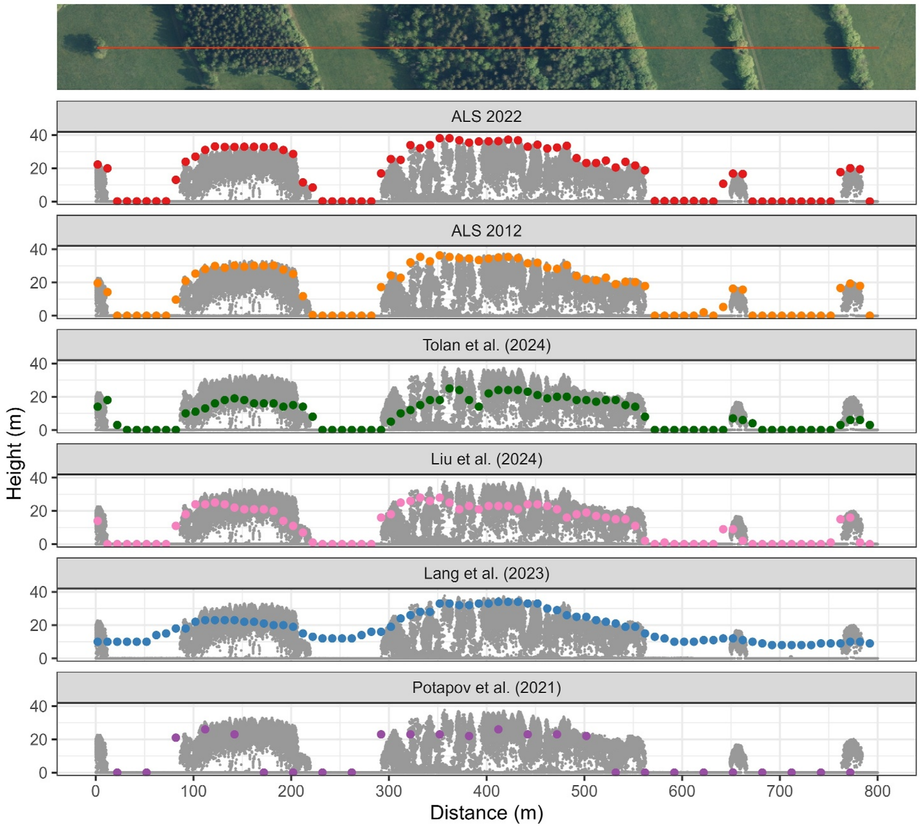

Figure 1. A representative canopy height profile (10 m deep) from the Giant Mountains National Park, Czechia. Note the limited ability, especially in the CHM by Lang et al. (2023), to capture variations in canopy height, making the transition between forest and non-forest areas unclear. The mosaic of pastures and forests appears as a continuous forest with heights ranging from 10 to 30 m. In contrast, the CHMs by Tolan et al. (2024) and Liu et al. (2023) 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 resolution of the CHM by Potapov et al. (2021) is too coarse to capture smaller stands.

validation studies. For example, Chen et al. (2025) and Ng et al. (2025) highlighted limitations and notable accuracy differences in global CHMs over China and New Zealand, respectively. Similarly, Dong, Xu, et al. (2025) identified consistent limitations across products, including widespread canopy misclassification, and systematic biases in canopy height predictions in urban environments. Importantly, all studies indicate that low canopies are typically overestimated and high canopies are underestimated, resulting in a limited ability of predicted CHMs to capture canopy height variability (Chen et al., 2025; Dong, Xu, et al., 2025; Moudrý, Gábor, et al., 2024; Ng et al., 2025). Together, these findings illustrate that despite recent progress, substantial uncertainty remains in predicted CHM products (Besic et al., 2025; Lencinas, 2025).

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 spaceborne data-based CHMs to reference heights extracted from ALS CHMs. Both large over- and underestimation of vegetation height can be observed in spaceborne CHMs (Figure 1; see Moudrý, Gábor, et al. (2024) for evaluation in other temperate forests). The continental canopy height map for Europe (Liu et al., 2023) exhibited a lower root mean square error than the three global products (Figure 2), consistent with the results of a recent comparison of the same CHMs conducted by Fogel et al. (2025). However, the change in vegetation height over 10 years is lower than the canopy height error in the four models for the selected area (Figure 2). In this example, such an error hinders effective change detection in canopy height. This limitation can be further influenced by the amount of disturbance, which is relatively low in our study area (Figure 2). In cases of

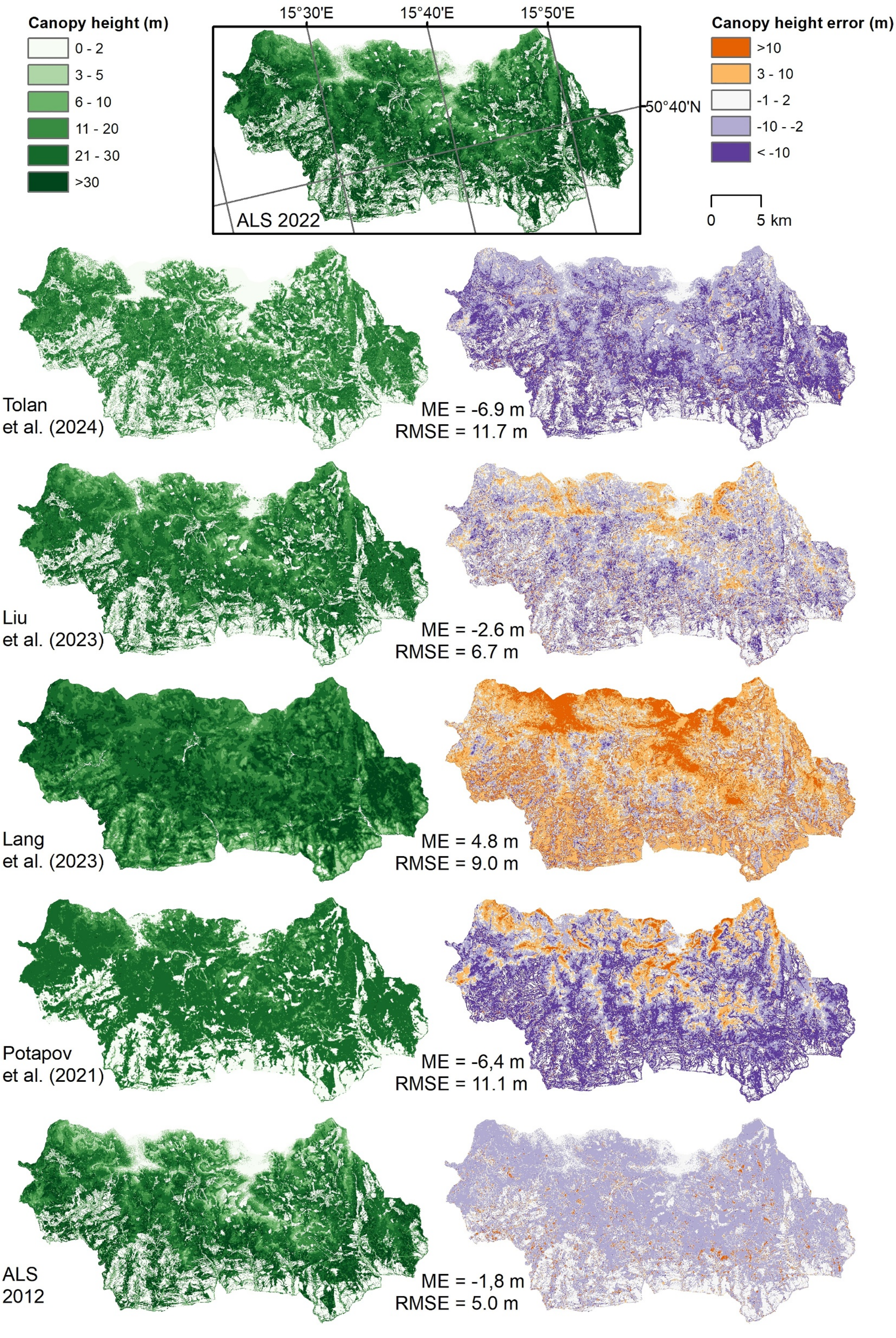

Figure 2. Canopy heights from four predicted canopy height maps from spaceborne LiDAR: Tolan et al. (2024), Liu et al. (2023), Lang et al. (2023), and Potapov et al. (2021) and an outdated (2012) ALS compared with a recent (2022) ALS model (reference data set). The figures on the left show canopy height, 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.

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 vegetation height before such disturbances occur.

3.2. What to Report and Consider When Generating and Using CHMs

Global CHM data sets are indispensable for answering large-scale ecological questions, and with the increasing availability of suitable data, the number of such products will continue to grow (Lencinas, 2025). It is, therefore, imperative to improve the reporting of accuracy and uncertainty in predicted CHMs. In addition, new products should be routinely compared with existing ones to identify systematic discrepancies between products and to enable users to select the most appropriate data set for their purposes (e.g., Markonis et al., 2024). A detailed discussion of validation approaches is beyond the scope of this study. However, the Committee on Earth Observation Satellites (CEOS) protocol for biomass products provides a useful reference for best practices in estimating and reporting uncertainties, and similar principles can be applied to CHM products (Duncanson et al., 2021).

To select the best vegetation structure product, the overall evaluation metrics (e.g., Höhle & Höhle, 2009), 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. Rather than relying on a few individual metrics, products should provide a spatially explicit uncertainty layer; however, this is rarely implemented. The study by Lang et al. (2023) is a notable exception, explicitly evaluating both model and data uncertainty. Model uncertainty reflects uncertainty in the learned relationships and the model's ability to generalize beyond the conditions represented in the calibration data. Indeed, unevenly distributed calibration data can force the model to make predictions under conditions not represented during training, leading to invalid or unreliable predictor–response relationships. This issue is typical of CHMs developed using ALS data, as available samples typically do not capture the full range of ecosystems (e.g., Liu et al., 2023; Wagner et al., 2025). One way to improve the reporting of such uncertainties is to assess the area to which a prediction can be reliably applied. Methods such as the Area of Applicability (Meyer & Pebesma, 2021) inform users about regions where the predictor space resembles the training data, thereby reducing the risk of extrapolation-driven errors. In addition, uncertainty can arise from discrepancies in the data, such as between the true canopy height and the height measured by the satellite (or airborne) LiDAR sensors. These discrepancies are mainly caused by co-registration errors and by measurement inaccuracies of the sensor. These issues are particularly relevant for satellite LiDARs (e.g., Lahssini et al., 2024; Moudrý, Prošek, et al., 2024; Urbazaev et al., 2022). Another factor contributing to data uncertainty may be the discrepancy between the size of the LiDAR footprint and the spatial resolution of predictors (e.g., CHMs are often produced at a 10 m resolution, whereas the GEDI footprint is 25 m in diameter).

Importantly, uncertainty estimates themselves must be validated; recent findings show that the uncertainty layer of the global CHM by Lang et al. (2023) is inaccurate (see supplementary material in Moudrý, Gábor, et al., 2024). This can be easily added, for example, by comparing the estimated uncertainty with the error observed in the CHM relative to more accurate validation data (e.g., ALS). Furthermore, we suggest that in addition to validation with ALS data, the predicted CHM products should include representative profiles (as in Figure 1) in addition to standard 2D visualizations. Most authors of the global data sets only showed product visualizations in 2D space (e.g., Lang et al., 2023; Potapov et al., 2021; Schwartz et al., 2023), which can make even poorly performing models appear plausible (Figure 2). Vertical cross-sections reveal structural inconsistencies and over- or underestimation patterns that are otherwise hidden in 2D, thereby helping users better understand model limitations and associated uncertainty. Finally, ALS data are increasingly available worldwide (e.g., Fischer et al., 2025); users can validate global CHMs in representative regions, helping to select the most suitable product when multiple CHMs are available for a given region.

4. Continuous Mapping of the Earth's Surface by Integrating Airborne and Satellite Data

In contrast to costly and typically infrequent ALS campaigns (though see the next section), satellite data provide frequent, contiguous coverage, enabling dynamic estimation of vegetation structure. A potential solution to providing global fine-resolution data on the vertical structure of vegetation 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). Such a constellation would enable consistent and repeatable monitoring of vegetation structure dynamics at a global scale. Hancock et al. (2021) estimated that producing such continuous data at a 30 m resolution every 5 years would require a constellation of 12 satellites acting concurrently. More recently, Lowe et al. (2024) investigated which platform-optics-constellation design offers the most promising and cost-effective solution, and suggested that micro-satellites, with a mass in 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-m resolution annually. The development of such a satellite constellation was announced relatively recently by the geospatial technology startup NUVIEW, which aims to deploy 20 commercial satellites equipped with LiDAR to map the Earth's entire land surface annually. In addition, NASA currently has an advanced proposal for the next-generation spaceborne laser altimetry mission, known as Earth Dynamics Geodetic Explorer (EDGE), which aims to significantly improve spatial accuracy and coverage, vertical precision, and change detection.

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. Therefore, the assessment of vegetation structure (e.g., canopy height) and its changes at fine resolution will continue to rely on data fusion approaches in the foreseeable future (Valbuena et al., 2020). However, this remains a challenging task (see reviews by Coops et al., 2021; Balestra et al., 2024). To improve the accuracy and reliability of such fused products (see the previous section on the limitations of existing ones), continued development and refinement of modeling approaches are essential. This requires exploring and testing new algorithms, as recently demonstrated by Fogel et al. (2025), who evaluated the applicability of computer vision models for this purpose and suggested that transformer-based architectures exhibit superior performance. Moreover, the increasing availability of suitable auxiliary data sets from recent satellite missions, such as NASA-ISRO Synthetic Aperture Radar (NISAR) and the European Space Agency (ESA) Biomass mission (note, however, that Biomass mission data are not available over Europe and North America), is also expected to improve estimates of vegetation characteristics (e.g., Silva et al., 2021; Valbuena et al., 2020). In the relatively near future, these efforts may also benefit from planned missions, such as Landsat Next, which is expected to offer more spectral bands and improved spatial resolution compared to previous Landsat missions (Roy et al., 2026). Finally, continued refinement of GEDI and ICESat-2 data processing is also valuable, as they do not yet provide perfect ground truth. Some of the error in predicted CHMs likely stems from the limited accuracy with which both GEDI and ICESat-2 can measure terrain and canopy height (Lahssini et al., 2024; Moudrý, Prošek, et al., 2024; Pracná et al., 2025; Urbazaev et al., 2022). Enhancing the accuracy of data produced by these missions requires high-quality benchmark data sets, and ALS data represent an indispensable source for this purpose (e.g., Duncanson et al., 2019; Tang et al., 2023). Indeed, even if we manage to build a constellation of LiDAR satellites capable of dense spatio-temporal mapping of vegetation structure in the near future, it will need precise and consistent benchmark data sets over large geographical areas for its calibration and validation.

ALS data are also crucial for training and validating data fusion models (Balestra et al., 2024; Fogel et al., 2025), yet the lack of open-access high-resolution data sets hinders the reproducibility and evaluation of models (Fogel et al., 2025). When combined with very high-resolution satellite imagery, ALS data further enable canopy height prediction at spatial resolutions of up to 1 m (e.g., Tolan et al., 2024; Wagner et al., 2025), which can be particularly useful for extending coverage to areas where ALS data are currently unavailable (see the next section). Furthermore, the current status of vegetation structure derived from ALS data is essential for assessing changes, either in combination with direct observations from satellite LiDAR (Guerra-Hernández & Pascual, 2021; Parra & Simard, 2023) or through predicted CHMs (Fogel et al., 2025; Pauls et al., 2025). For all these reasons, available state- and country-wide ALS data represent the cornerstone for advancing global vegetation structure mapping—serving as a benchmark for future spaceborne missions, a driver of innovation in modeling and data fusion, and a source for immediate monitoring needs. They should, therefore, be used to produce uniform, seamless vegetation structure products.

5. Toward European Canopy Height Model Derived From Airborne Laser Scanning Data

Unlike spaceborne laser altimeters, which offer broader coverage but discrete and sparse measurements (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 large-scale analyses covering multiple countries (Fischer et al., 2024). As a result, large-scale studies are impeded by the absence of consistent, accurate, and accessible vegetation structure data, and generally rely on global predicted products from satellites (see Section 3) due to the difficulties in managing and processing ALS data at a continental scale.

The United States sets a good example with the 3D Elevation Program (3DEP), managed by the U.S. Geological Survey (USGS), which aims to collect ALS data for the conterminous United States, following specific collection requirements to ensure consistent LiDAR coverage across the entire territory (USGS, 2024). So far, however, it only aims at providing a digital terrain model (DTM; Stoker, 2020; Stoker & Miller, 2022), not seamless CHMs (or other vegetation structure products) in a raster format. Digital surface models (DSMs) could, however, be created through OpenTopography (https://opentopography.org/), where most U.S. LiDAR data are also hosted. Europe is lagging behind, as no common data collection requirements or methodology that regulates mapping activities exists. This responsibility falls to the individual states and countries. As a result, ALS coverage in Europe is managed at the national (e.g., in Denmark, France, Netherlands, 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).

Of the 44 countries in Europe, ALS data are collected by governmental institutions in at least 33 countries (Figures 3 and 4; see Supporting Information S1 for more details on ALS campaigns in individual countries). However, national ALS acquisitions are typically designed to capture terrain information rather than vegetation structure, which means that the data are often collected using acquisition parameters that are suboptimal for characterizing vegetation structure (e.g., low point densities or acquisitions under the leaf-off period). Notable exceptions are France's LiDAR HD program, carried out by the Institut National de l'Information Géographique et Forestière (IGN, https://geoservices.ign.fr/lidarhd), with dedicated summer acquisitions for forest resource assessments, and a recent effort by the Federal Agency for Cartography and Geodesy of Germany, which aims to map the entire Germany under leaf-on conditions and with point cloud density of 40 points per square meter between 2024 and 2025 as a part of the Digital Twin Germany initiative (GIM International, 2025; Hopfstock et al., 2022).

At the moment, only a few European countries provide ALS-derived metrics of vegetation structure in a raster format (Denmark, Netherlands, and Switzerland; see Assmann et al., 2022; Kissling et al., 2023; Külling et al., 2024; Shi et al., 2025). These products typically include dozens of vegetation structure metrics describing, for example, vegetation cover and density (often separated into vertical strata), as well as various measures of vertical structural variability, such as skewness, kurtosis, or the coefficient of variation of vegetation height. Nevertheless, the choice of vegetation metrics, the methods used to calculate them, and their resolution can vary significantly among products (Cosgrove et al., 2024; Kissling & Shi, 2023; Moudrý et al., 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 transnational, Europe-wide product. Such a harmonized product 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 across broad spatial extents.

Achieving this, however, will require addressing several challenges that currently limit the production of consistent and reliable products: (a) inconsistencies in acquisition characteristics and classification accuracy across data sets and countries, (b) 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) and differences in coordinate reference systems, and (c) availability and reliability of (meta)data. Below, we illustrate these challenges using the example of creating a near-continental CHM from existing ALS data, which we consider the first step toward this broader goal.

5.1. Inconsistencies in Acquisition Characteristics and Classification Accuracy

Combining LiDAR data from different campaigns presents challenges, as the three-dimensional structure of the point cloud, and consequently vegetation structural metrics, can vary with acquisition characteristics (Fischer et al., 2024; Goodwin et al., 2007; Roussel et al., 2017; Wulder et al., 2012; Zhang et al., 2024). These inconsistencies can, however, be mitigated by systematically evaluating how LiDAR-derived vegetation metrics

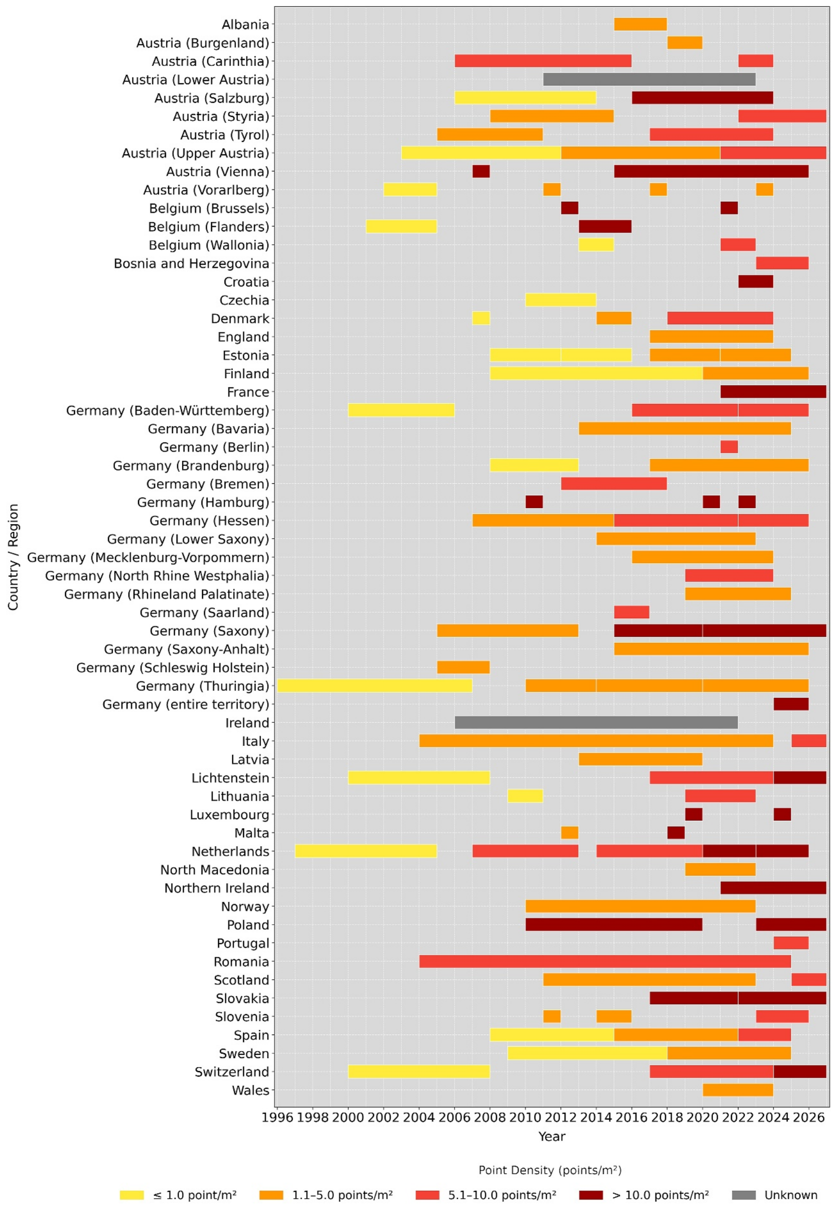

Figure 3. Years of acquisition of airborne laser scanning campaigns conducted by governmental institutions in Europe, including point density information where available. Note that the information provided is likely incomplete, both in terms of available data and their metadata, as these are documented 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, and whether these are nominal/minimal densities or realized densities (which are often higher). Therefore, we use the single term point density.

respond to changes in factors such as spatial resolution, pulse density, and scan angle, and by selecting an appropriate resolution for the final product (e.g., Kissling et al., 2024; Shi et al., 2025; van Lier et al., 2022).

The typical point densities of LiDAR point clouds available in Europe are around 5–10 points per square meter (see Figure 3 in Kissling et al., 2024); still, they vary considerably across the continent (Figures 3 and 4). For low point densities, it is advisable to calculate vegetation metrics at coarser resolutions (e.g., 10 or 20 m) to minimize potential errors in estimating the vegetation structure (D'Amico et al., 2021; Kamoske et al., 2019; Kissling et al., 2024; Ruiz et al., 2014; Wilkes et al., 2015). On the other hand, vegetation metrics, such as upper percentiles of height, are generally less sensitive to point cloud properties (Fischer et al., 2024; Kissling et al., 2024; LaRue

10.1029/2025EA004544

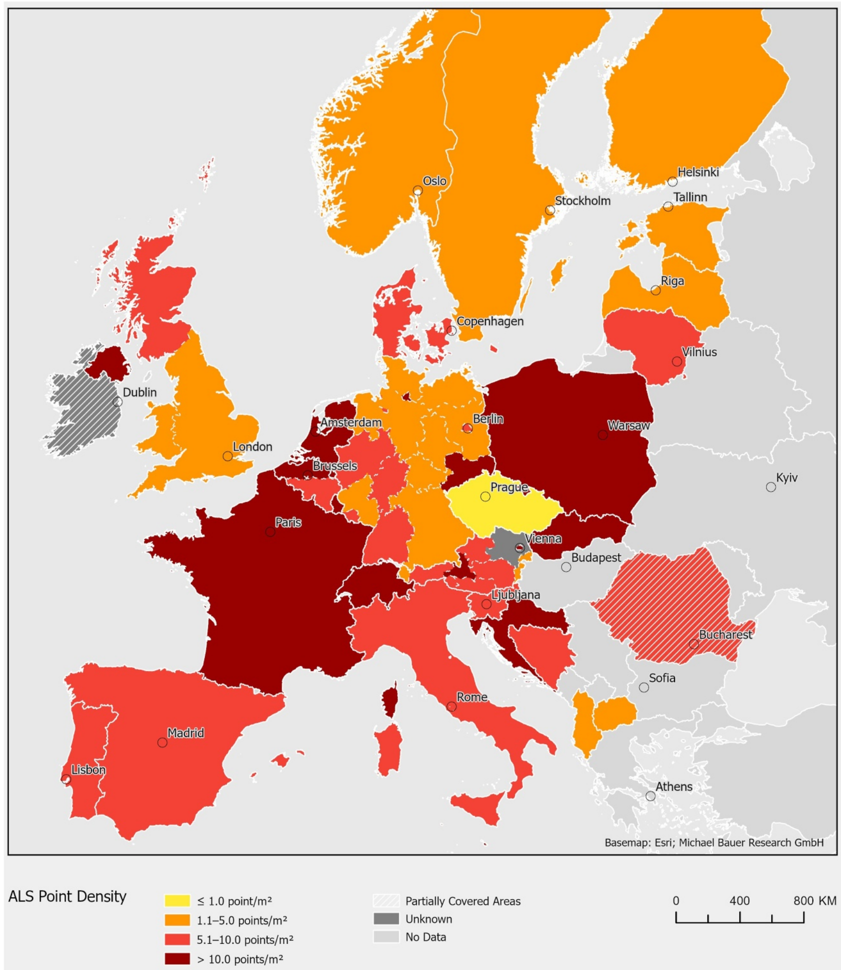

Figure 4. Coverage of Europe by airborne laser scanning campaigns conducted by governmental institutions, including information on point densities from the latest campaigns where available. Note that, to illustrate the overall extent of ALS data availability in Europe, we also show countries where national scanning is currently underway as fully covered, even though completion is expected only within the next one or 2 years (i.e., France, Italy, Northern Ireland; Scotland; see Figure 3 and Supporting Information S1 for more details).

et al., 2022; Roussel et al., 2017), and deriving a CHM at a 10-m 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, constitutes another factor. While classes such as ground, low/medium/high vegetation, building, water, and unclassified are most commonly available in open-access ALS data across Europe, power lines, bridges, and viaducts are less often included (see Figure 3d in Kissling et al., 2024), potentially introducing bias in vegetation metrics (Shi & Kissling, 2023). However, this may not be a major issue if the focus is primarily on forests or nature reserves, where even less accurate classifications can still provide better results than predicted CHMs.

The scan angle of the laser pulses is another factor that has to be considered. The use of wider scan angles expands the swath width, allowing larger areas to be surveyed and potentially helping to optimize costs. However, as scan angles increase, the laser pulse travels a longer path through the canopy, increasing the likelihood of striking upper-canopy and reducing the probability of reaching the ground (e.g., Disney et al., 2010; Goodwin et al., 2007; Montaghi, 2013). With wider scan angles, the canopy effectively appears denser under otherwise identical acquisition conditions, which can, in turn, introduce bias into vegetation-structure metrics (Roussel et al., 2018). Although small deviations from nadir (up to approximately 15°–20°) generally have little effect on maximum canopy height or upper percentiles metrics, larger off-nadir angles can introduce biases, particularly for metrics such as lower height percentiles or gap fraction (Dayal et al., 2020; Liu et al., 2018; Montaghi, 2013; van Lier et al., 2022). Moreover, the effect of scan angle is influenced by the vegetation structure itself (e.g., by species composition and crown shapes; Liu et al., 2018; van Lier et al., 2022). In general, the impact of scan angle is modest and largely mitigated by overlapping flight lines and increased point density (Dayal et al., 2022; Lovell et al., 2005; van Lier et al., 2022). For instance, national ALS in Sweden requires the use of maximum scan angles of ±20°, whereas Slovenia allows angles up to ±30°. This highlights the need to account for scan angle to minimize systematic biases (Roussel et al., 2018), particularly when combining data sets from different ALS campaigns, such as country-wide surveys in Europe, or when using multi-temporal ALS data (Liu et al., 2018; Montaghi, 2013; Riofrío et al., 2022).

Additional acquisition characteristics, while beyond the scope of this study, may also influence the structure of ALS point clouds and derived vegetation metrics. For example, the wavelength of the laser pulse can affect canopy penetration and backscatter intensity (Lefsky et al., 2002). Similarly, the total power of the transmitted pulse (i.e., pulse width) and footprint size can further modulate how the laser interacts with vegetation, potentially altering the representation of vegetation structure in the point cloud (e.g., Hovi & Korpela, 2014). While these parameters may introduce differences, their effects are typically secondary compared to above mentioned scan angle and point density. Likewise, differences between sensor technologies, such as linear-mode versus single-photon LiDAR (White et al., 2021), can introduce additional variability. However, to our knowledge, single-photon LiDAR has so far seen very limited use in large-scale ALS acquisitions across Europe, with the likely exception of ongoing surveys in Germany between 2024 and 2025 for the Digital Twin initiative.

5.2. Temporal Inconsistency and Differences in Coordinate Reference Systems

The temporal inconsistency of ALS data acquisition across countries is a concern, as ALS surveys remain costly and infrequent. Moreover, ALS data collection often predominantly aims to provide accurate topographic modeling, so many countries carry out scans under leaf-off conditions (such as Slovenia, England, Czechia, and the Netherlands). In some countries, however, scanning is explicitly timed to occur close to the peak vegetation greenness (e.g., Estonia), while in other countries it depends on the region (e.g., Spain). Some countries may even merge point clouds across different scanning periods (France). Therefore, the density of vegetation returns may vary considerably depending on when the data were collected. If unaccounted for, the resulting differences could introduce substantial bias and limit the usability and accuracy of harmonized vegetation structure maps. In addition, as new advancements in scanning technology emerge (e.g., higher pulse repetition frequency, wider scan angles, use of multiple wavelengths, and different sensor types), older data sets can become less compatible with current data (i.e., due to considerable differences in acquisition characteristics), 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 16 years (2010–2025; Figure 3). While this is not optimal, a 10-year difference can introduce (as illustrated above) less error than the predicted maps (Figure 2), if the area under study did not experience major disturbance events. 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. In addition, higher observation frequencies in hotspots (e.g., areas experiencing considerable disturbances) could enhance the applicability of ALS data for timely management decisions (e.g., Fassnacht et al., 2024; Kissling et al., 2024).

The standardization of coordinate reference systems (both horizontal and vertical) is another important aspect in creating a near-continental CHM across Europe. Europe is historically fragmented in terms of coordinate reference systems, with individual countries having developed their own horizontal and vertical datums, which adds complexity to creating a unified CHM and can introduce misalignments and inconsistencies when merging point clouds. Ensuring that all data sets are converted to a common horizontal and vertical reference system is, therefore, a prerequisite for producing seamless and accurate CHMs at a continental scale. Ideally, all ALS data across Europe should be available in the ETRS89 reference system with ellipsoidal heights referenced to the GRS80 ellipsoid (i.e., the system in which all ALS data across Europe are originally acquired, since the positions of the aircraft collecting the data are determined using differential Global Navigation Satellite Systems methods relying on reference station networks realized in this system). Nevertheless, for distribution to end users, ALS point clouds are typically converted into local horizontal projected coordinate systems and either orthometric heights (e.g., in Spain) or normal heights (e.g., in Czechia), and access to the original ETRS89 data is, in most cases, complicated.

Standardizing vertical reference systems to a single unified system requires access to all local geoid or quasi-geoid heights (i.e., undulations) to enable conversion of the data to ellipsoidal heights. However, this can be challenging, as geoid or quasi-geoid data are not freely available in many countries. Fortunately, in the specific case of vegetation metrics such as canopy height, which express relative height above the ground rather than absolute height above sea level, the issue of unifying vertical reference systems can effectively be ignored. Although not ideal, a similar solution is also often used when combining multitemporal ALS acquisitions (Riofrío et al., 2022). This, of course, does not apply when creating a continental DTM, and although focusing here solely on vegetation structure allows us to largely circumvent this issue, we acknowledge that local geoid (and quasi-geoid) information will eventually be necessary for fully unified elevation products. In the first step, point clouds should be transformed into the same horizontal coordinate reference system (e.g., ETRS89) and height-normalized. Subsequently, the CHM can be obtained using any existing method (Fisher et al., 2024). Alternatively, these steps can be reversed, and the transformation applied to raster data after the CHM (or other vegetation metric) generation. This approach may be necessary in the case of countries where point cloud data are not freely available, but raster-based DSM and DTM products are accessible.

5.3. (Meta)Data Availability and Reliability

Although the data have different characteristics as mentioned above, it is possible to derive vegetation structure metrics in raster format at a relatively fine resolution (Assmann et al., 2022; Kissling et al., 2023; Shi et al., 2025). This requires detailed documentation of the metadata in order to develop standardized processing pipelines that can account for differences in scanning properties (Fischer et al., 2024). 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 (see Supporting Information S1), 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. Therefore, in line with the FAIR guiding principles (Wilkinson et al., 2016), it is important that ALS surveys provide standardized, machine-readable metadata of survey variables and sensor characteristics, as well as documentation of preprocessing steps and provenance of (sub)national ALS point cloud data sets (Kissling et al., 2024). For ecological applications, it is also important to provide the flight line time-stamps in a spatially explicit way because the actual date/month during which an area is scanned can vary within a national ALS data set (Shi et al., 2025).

In addition, in many cases, accessing the data itself remains challenging. Point clouds are still not freely available in several European states (e.g., Austria, Bosnia and Hercegovina, Romania, Malta), may not be easily accessible through web interfaces and require formal requests for release (e.g., Croatia), or the portals may be difficult to log into (e.g., Montenegro). Furthermore, while ALS data have been collected over multiple time periods in some parts of Europe (Figure 3), and countries such as Estonia, the Netherlands, and Spain openly provide all existing data, in other areas, only the data from the most recent period are easily accessible (e.g., Saxony, Switzerland). Hence, establishment of a centralized repository, and creation of a metadata catalog with human- and machine-readable metadata would be a major step forward (Kissling et al., 2024). Access to funding will be a crucial factor in this effort. A European funding initiative similar to 3DEP, supported by the EU, would be a good approach to generate vegetation structure metrics from existing data, to establish a centralized repository, 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.

6. Conclusions and Outlook

The availability of remote sensing data greatly facilitates forestry and ecological research. On the other hand, the growing number of data sets of varying quality introduces challenges regarding which data sets 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 data sets. Predicted CHM products should provide reliable uncertainty estimates and visualizations of vegetation profiles (Figure 1) for representative areas and ecosystems.

For vegetation structure, accurate, consistent, and repeatable continental products derived from ALS data are key and should be prioritized over predicted spaceborne products. We strongly recommend that ALS-rich regions prioritize the production of ALS-based canopy height maps over relying solely on modeled global data. In Europe, the first step lies in creating a near-continental CHM using existing data (Figure 4), which, even given the differences in the data collected, is possible at a reasonably fine spatial (e.g., 10–20 m) and temporal (e.g., 15 years) resolution. While canopy height represents a key structural attribute, it should be viewed as only the first step toward a broader objective. The next step lies in expanding this coordinated effort to encompass additional ALS-based metrics (e.g., skewness, kurtosis, and the coefficient of variation of vegetation height, as well as vegetation density and cover; Moudrý et al., 2023; Kissling & Shi, 2023), thus enabling a more comprehensive assessment of ecosystem structure.

To ensure the effective use of ALS across Europe in the future, better transnational coordination is needed. It is necessary to establish a common data collection protocol to harmonize mapping activities (e.g., time of acquisition, pulse density, update period), a centralized repository for data sharing, as well as a metadata catalog. A European-wide coordination of data collection would lead to improved forest management, ecosystem monitoring, and climate change modeling on a continental scale. Beyond forestry and ecology, such data would also provide a valuable foundation for numerous other disciplines—including geomorphology, hydrology, and urban studies—where detailed and consistent 3D information on terrain, vegetation, and built structures is essential. Finally, they would provide a benchmark for calibrating spaceborne laser altimetry products.

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. WDK acknowledges the MAMBO project funded by the European Commission (grant agreement number 101060639). We are grateful to Ada Perello for providing information on laser scanning campaigns in several European countries.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

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 (Moudrý, 2024).

References

Abshire, J. B., Sun, X., Riris, H., Sirota, J. M., McGarry, J. F., Palm, S., et al. (2005). Geoscience laser altimeter system (GLAS) on the ICESat mission: On-orbit measurement performance. *Geophysical Research Letters*, *32*(21). https://doi.org/10.1029/2005gl024028

Alvites, C., O'Sullivan, H., Saverio, F., Marco, M., Santopuoli, G., Chirici, G., et al. (2025). Canopy height mapper: A Google Earth Engine application for predicting global canopy heights combining GEDI with multi-source data. *Environmental Modelling & Software*, *183*, 106268. https://doi.org/10.1016/j.envsoft.2024.106268

Anderle, M., Brambilla, M., Hilpold, A., Matabishi, J. G., Paniccia, C., Rocchini, D., et al. (2023). Habitat heterogeneity promotes bird diversity in agricultural landscapes: Insights from remote sensing data. *Basic and Applied Ecology*, *70*, 38–49. https://doi.org/10.1016/j.baae.2023.04.006

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. https://doi.org/10.5194/essd-14-823-2022

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. https://doi.org/10.1002/2017jg004256

Balestra, M., Marselis, S., Sankey, T. T., Cabo, C., Liang, X., Mokroš, M., et al. (2024). LiDAR data fusion to improve forest attribute estimates: A review. *Current Forestry Reports*, *10*(4), 281–297. https://doi.org/10.1007/s40725-024-00223-7

Bergen, K. M., Goetz, S. J., Dubayah, R. O., Henebry, G. M., Hunsaker, C. T., Imhoff, M. L., et al. (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*, *114*(G2). https://doi.org/10.1029/2008jg000883

Besic, N., Picard, N., Vega, C., Bontemps, J. D., Hertzog, L., Renaud, J. P., et al. (2025). Remote-sensing-based forest canopy height mapping: Some models are useful, but might they provide us with even more insights when combined? *Geoscientific Model Development*, *18*(2), 337–359. https://doi.org/10.5194/gmd-18-337-2025

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. https://doi.org/10.5589/m13-036

Brodie, J. F., Mohd-Azlan, J., Chen, C., Wearn, O. R., Deith, M. C., Ball, J. G., et al. (2023). Landscape-scale benefits of protected areas for tropical biodiversity. *Nature*, *620*(7975), 807–812. https://doi.org/10.1038/s41586-023-06410-z

Burns, P., Hakkenberg, C., & Goetz, S. J. (2024). *Gridded GEDI vegetation structure metrics and biomass density at multiple resolutions*. ORNL DAAC. https://doi.org/10.3334/ORNLDAAC/2339

Caynes, R. J., Mitchell, M. G., Wu, D. S., Johansen, K., & Rhodes, J. R. (2016). Using high-resolution LiDAR data to quantify the three-dimensional structure of vegetation in urban green space. *Urban Ecosystems*, *19*(4), 1749–1765. https://doi.org/10.1007/s11252-016-0571-z

Ceccherini, G., Girardello, M., Beck, P. S., Migliavacca, M., Duveiller, G., Dubois, G., et al. (2023). Spaceborne LiDAR reveals the effectiveness of European protected areas in conserving forest height and vertical structure. *Communications Earth & Environment*, *4*(1), 97. https://doi.org/10.1038/s43247-023-00758-w

Chen, A., Cheng, K., Chen, Y., Qi, Z., Yang, H., Ren, Y., et al. (2025). Validating recent global canopy height maps over China's forests based on UAV LiDAR data. *Remote Sensing of Environment*, *329*, 114957. https://doi.org/10.1016/j.rse.2025.114957

Clark, M., Hakkenberg, C. R., Bailey, T., Burns, P., & Goetz, S. J. (2025). Changes in GEDI-based measures of forest structure after large California wildfires relative to pre-fire conditions. *Remote Sensing of Environment*, *323*, 114718. https://doi.org/10.1016/j.rse.2025.114718

Coops, N. C., Tompalski, P., Goodbody, T. R., Queinnec, M., Luther, J. E., Bolton, D. K., et al. (2021). Modelling LiDAR-derived estimates of forest attributes over space and time: A review of approaches and future trends. *Remote Sensing of Environment*, *260*, 112477. https://doi.org/10.1016/j.rse.2021.112477

Cosgrove, C. F., Coops, N. C., & Martin, T. G. (2024). Using the full potential of Airborne Laser Scanning (aerial LiDAR) in wildlife research. *Wildlife Society Bulletin*, *48*(3), e1532. https://doi.org/10.1002/wsb.1532

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. https://doi.org/10.1111/1365-2745.14068

D'Amico, G., Vangi, E., Francini, S., Giannetti, F., Nicolaci, A., Travaglini, D., et al. (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*(2), 144–154. https://doi.org/10.3832/ifor3648-014

Davies, A. B., & Asner, G. P. (2014). Advances in animal ecology from 3D-LiDAR ecosystem mapping. *Trends in Ecology & Evolution*, *29*(12), 681–691. https://doi.org/10.1016/j.tree.2014.10.005

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. https://doi.org/10.1111/1365-2656.13945

Dayal, K. R., Durrieu, S., Alleaume, S., Revers, F., Larmanou, E., Renaud, J. P., & Bouvier, M. (2020). Scan angle impact on LiDAR-derived metrics used in ABA models for prediction of forest stand characteristics: A grid based analysis. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 975–982. https://doi.org/10.5194/isprs-archives-xliii-b3-2020-975-2020

Dayal, K. R., Durrieu, S., Lahssini, K., Alleaume, S., Bouvier, M., Monnet, J. M., et al. (2022). An investigation into LiDAR scan angle impacts on stand attribute predictions in different forest environments. *ISPRS Journal of Photogrammetry and Remote Sensing*, *193*, 314–338. https://doi.org/10.1016/j.isprsjprs.2022.08.013

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. https://doi.org/10.1080/07038992.2024.2341762

Disney, M. I., Kalogirou, V., Lewis, P., Prieto-Blanco, A., Hancock, S., & Pfeifer, M. (2010). Simulating the impact of discrete-return LiDAR system and survey characteristics over young conifer and broadleaf forests. *Remote Sensing of Environment*, *114*(7), 1546–1560. https://doi.org/10.1016/j.rse.2010.02.009

Dong, H., Tang, L., Liu, J., Hu, X., & Shao, G. (2025). Remote sensing of urban tree carbon stocks: A methodological review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *227*, 570–593. https://doi.org/10.1016/j.isprsjprs.2025.06.030

Dong, H., Xu, Z., Wu, J., Lan, T., Wang, L., Shao, G., & Tang, L. (2025). High-precision airborne LiDAR remains essential for urban forestry: Revealing the limitations of recent large-scale canopy height products in urban contexts. *International Journal of Applied Earth Observation and Geoinformation*, *143*, 104791. https://doi.org/10.1016/j.jag.2025.104791

Dubayah, R., Blair, J. B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., et al. (2020). The Global Ecosystem Dynamics Investigation: High-resolution laser ranging of the Earth's forests and topography. *Science of Remote Sensing*, *1*, 100002. https://doi.org/10.1016/j.srs.2020.100002

Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., et al. (2019). The importance of consistent global forest aboveground biomass product validation. *Surveys in Geophysics*, *40*(4), 979–999. https://doi.org/10.1007/s10712-019-09538-8

Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., et al. (2021). Aboveground woody biomass product validation good practices protocol. Version 1.0. In *Good practices for satellite derived land product validation* (pp. 1–236). https://doi.org/10.5067/doc/ceoswgcv/lpv/agb.001

European Commision. (2021). *New EU forest strategy for 2030*. Publications Office of the European Union. Retrieved from https://commission.europa.eu/document/cf3294e1-8358-4c93-8de4-3e1503b95201_en

Fassnacht, F. E., Mager, C., Waser, L. T., Kanjir, U., Schäfer, J., Buhvald, A. P., et al. (2025). Forest practitioners' requirements for remote sensing-based canopy height, wood-volume, tree species, and disturbance products. *Forestry: An International Journal of Forest Research*, *98*(2), 233–252. https://doi.org/10.1093/forestry/cpae021

Fassnacht, F. E., White, J. C., Wulder, M. A., & Næsset, E. (2024). Remote sensing in forestry: Current challenges, considerations and directions. *Forestry: An International Journal of Forest Research*, *97*(1), 11–37. https://doi.org/10.1093/forestry/cpad024

Fernandez-Diaz, J. C., Velikova, M., & Glennie, C. L. (2022). Validation of ICESat-2 ATL08 terrain and canopy height retrievals in tropical Mesoamerican forests. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 2956–2970. https://doi.org/10.1109/jstars.2022.3163208

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*, *15*(10), 1873–1888. https://doi.org/10.1111/2041-210x.14416

Fischer, F. J., Morgan, B., Jackson, T., Chave, J., Coomes, D., Cushman, K. C., et al. (2025). The Global Canopy Atlas: Analysis-ready maps of 3D structure for the world's woody ecosystems. *bioRxiv*.

Fischer, R., Knapp, N., Bohn, F., Shugart, H. H., & Huth, A. (2019). The relevance of forest structure for biomass and productivity in temperate forests: New perspectives for remote sensing. *Surveys in Geophysics*, *40*(4), 709–734. https://doi.org/10.1007/s10712-019-09519-x

Fogel, F., Perron, Y., Besic, N., Saint-André, L., Pellissier-Tanon, A., Schwartz, M., et al. (2025). Open-Canopy: Towards very high resolution forest monitoring. In *Proceedings of the Computer Vision and Pattern Recognition Conference* (pp. 1395–1406).

GIM International. (2025). Aerial survey for Germany's digital twin reaches halfway mark. Retrieved from https://www.gim-international.com/content/news/halfway-mark-for-germany-s-digital-twin-as-aerial-survey-reaches-50-percent

Gonzalez, A., Vihervaara, P., Balvanera, P., Bates, A. E., Bayraktarov, E., Bellingham, P. J., et al. (2023). A global biodiversity observing system to unite monitoring and guide action. *Nature Ecology & Evolution*, *7*(12), 1947–1952. https://doi.org/10.1038/s41559-023-02171-0

Goodwin, N. R., Coops, N. C., & Culvenor, D. S. (2007). Development of a simulation model to predict LiDAR interception in forested environments. *Remote Sensing of Environment*, *111*(4), 481–492. https://doi.org/10.1016/j.rse.2007.04.001

Grondard, N., van Bussel, L., & Hein, L. (2025). Monitoring woody landscape features in Dutch rural landscapes. *Ecological Indicators*, *178*, 113853. https://doi.org/10.1016/j.ecolind.2025.113853

Guenther, E., Neuenschwander, A. L., Jelley, B. P., & Robbins, J. W. (2024). Development towards ICESat-2 gridded land and vegetation data product (ATL18). In *AGU Fall Meeting Abstracts* (Vol. 2024, pp. B13C–1555).
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 and the Environment*, *21*(1), 55–56. https://doi.org/10.1002/fee.2585
Hancock, S., Lewis, P., Foster, M., Disney, M., & Muller, J. P. (2012). Measuring forests with dual wavelength LiDAR: A simulation study over topography. *Agricultural and Forest Meteorology*, *161*, 123–133. https://doi.org/10.1016/j.agrformet.2012.03.014
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. https://doi.org/10.1098/rsos.211166
Hawryło, P., Socha, J., Wężyk, P., Ochał, W., Krawczyk, W., Miszczyszyn, J., & Tymińska-Czabańska, L. (2024). How to adequately determine the top height of forest stands based on airborne laser scanning point clouds? *Forest Ecology and Management*, *551*, 121528. https://doi.org/10.1016/j.foreco.2023.121528
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. https://doi.org/10.1016/j.isprsjprs.2013.04.004
Herold, M., Carter, S., Avitabile, V., Espejo, A. B., Jonckheere, I., Lucas, R., et al. (2019). The role and need for space-based forest biomass-related measurements in environmental management and policy. *Surveys in Geophysics*, *40*(4), 757–778. https://doi.org/10.1007/s10712-019-09510-6
Höhle, J., & Höhle, M. (2009). Accuracy assessment of digital elevation models by means of robust statistical methods. *ISPRS Journal of Photogrammetry and Remote Sensing*, *64*(4), 398–406. https://doi.org/10.1016/j.isprsjprs.2009.02.003
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. https://doi.org/10.1016/j.rse.2024.114174
Hopfstock, A., Knöfel, P., & Lindl, F. (2022). Digital Twin Germany–a digital replica for simulation and analysis build on geospatial data. *Abstracts ICAAC*, *5*, 119.
Hovi, A., & Korpela, I. (2014). Real and simulated waveform-recording LiDAR data in juvenile boreal forest vegetation. *Remote Sensing of Environment*, *140*, 665–678. https://doi.org/10.1016/j.rse.2013.10.003
Janiec, P., Tymińska-Czabańska, L., Hawryło, P., Woda, M., & Socha, J. (2025). Determining vertical structure of forests in Poland using a semi-automated approach based on ALS data. *Ecological Indicators*, *178*, 113825. https://doi.org/10.1016/j.ecolind.2025.113825
Jucker, T., Gosper, C. R., Wiehl, G., Yeoh, P. B., Raisbeck-Brown, N., Fischer, F. J., et al. (2023). Using multi-platform LiDAR to guide the conservation of the world's largest temperate woodland. *Remote Sensing of Environment*, *296*, 113745. https://doi.org/10.1016/j.rse.2023.113745
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. https://doi.org/10.1016/j.fecs.2023.100146
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. https://doi.org/10.3390/rs13245105
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. https://doi.org/10.3390/rs15081969
Kakoulaki, G., Martinez, A., & Florio, P. (2021). *Non-commercial light detection and ranging (lidar) data in Europe*. Publications Office of the European Union.
Kamoske, A. G., Dahlin, K. M., Stark, S. C., & Serbin, S. P. (2019). Leaf area density from airborne LiDAR: Comparing sensors and resolutions in a temperate broadleaf forest ecosystem. *Forest Ecology and Management*, *433*, 364–375. https://doi.org/10.1016/j.foreco.2018.11.017
Kemppinen, J., Lembrechts, J. J., Van Meerbeek, K., Carnicer, J., Chardon, N. I., Kardol, P., et al. (2024). Microclimate, an important part of ecology and biogeography. *Global Ecology and Biogeography*, *33*(6), e13834. https://doi.org/10.1111/geb.13834
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. https://doi.org/10.1111/ddi.13760
Kissling, W. D., Shi, Y., Koma, Z., Meijer, C., Ku, O., Nattino, F., et al. (2022). Laserfarm–a high-throughput workflow for generating geospatial data products of ecosystem structure from airborne laser scanning point clouds. *Ecological Informatics*, *72*, 101836. https://doi.org/10.1016/j.ecoinf.2022.101836
Kissling, W. D., Shi, Y., Koma, Z., Meijer, C., Ku, O., Nattino, F., et al. (2023). Country-wide data of ecosystem structure from the third Dutch airborne laser scanning survey. *Data in Brief*, *46*, 108798. https://doi.org/10.1016/j.dib.2022.108798
Kissling, W. D., Shi, Y., Wang, J., Walicka, A., George, C., Moeslund, J. E., & Gerard, F. (2024). Towards consistently measuring and monitoring habitat condition with airborne laser scanning and unmanned aerial vehicles. *Ecological Indicators*, *169*, 112970. https://doi.org/10.1016/j.ecolind.2024.112970
Klouček, T., Klápště, P., Marešová, J., & Komárek, J. (2022). UAV-borne imagery can supplement airborne LiDAR in the precise description of dynamically changing Shrubland Woody vegetation. *Remote Sensing*, *14*(9), 2287. https://doi.org/10.3390/rs14092287
Koma, Z., Seijmonsbergen, A. C., & Kissling, W. D. (2021). Classifying wetland-related land cover types and habitats using fine-scale LiDAR metrics derived from country-wide Airborne Laser Scanning. *Remote Sensing in Ecology and Conservation*, *7*(1), 80–96. https://doi.org/10.1002/rse2.170
Külling, N., Adde, A., Fopp, F., Schweiger, A. K., Broennimann, O., Rey, P. L., et al. (2024). SWECO25: A cross-thematic raster database for ecological research in Switzerland. *Scientific Data*, *11*(1), 21. https://doi.org/10.1038/s41597-023-02899-1
Lahssini, K., Baghdadi, N., Le Maire, G., Fayad, I., & Villard, L. (2024). Canopy height mapping in French Guiana using multi-source satellite data and environmental information in a U-Net architecture. *Frontiers in Remote Sensing*, *5*, 1484900. https://doi.org/10.3389/frsen.2024.1484900
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. https://doi.org/10.1038/s41559-023-02206-6
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. https://doi.org/10.1002/ecs2.4209
LaRue, E. A., Fahey, R. T., Alveshere, B. C., Atkins, J. W., Bhatt, P., Buma, B., et al. (2023). A theoretical framework for the ecological role of three-dimensional structural diversity. *Frontiers in Ecology and the Environment*, *21*(1), 4–13. https://doi.org/10.1002/fee.2587
LaRue, E. A., Knott, J. A., Domke, G. M., Chen, H. Y., Guo, Q., Hisano, M., et al. (2023). Structural diversity as a reliable and novel predictor for ecosystem productivity. *Frontiers in Ecology and the Environment*, *21*(1), 33–39. https://doi.org/10.1002/fee.2586

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). https://doi.org/10.1029/2010gl043622

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. https://doi.org/10.1641/0006-3568(2002)052[0019:lrsfes]2.0.co;2

Lencinas, J. D. (2025). Assessing the accuracy of global canopy height models: A comprehensive review. *Bosque*, *46*(2), 129–140. https://doi.org/10.4067/s0717-92002025000200129

Li, W., Duveiller, G., Wieneke, S., Forkel, M., Gentine, P., Reichstein, M., et al. (2024). Regulation of the global carbon and water cycles through vegetation structural and physiological dynamics. *Environmental Research Letters*, *19*(7), 073008. https://doi.org/10.1088/1748-9326/ad5858

Liang, M., González-Roglich, M., Roehrdanz, P., Tabor, K., Zvoleff, A., Leitold, V., et al. (2023). Assessing protected area's carbon stocks and ecological structure at regional-scale using GEDI lidar. *Global Environmental Change*, *78*, 102621. https://doi.org/10.1016/j.gloenvcha.2022.102621

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. https://doi.org/10.1016/j.rse.2021.112571

Liu, J., Skidmore, A. K., Jones, S., Wang, T., Heurich, M., Zhu, X., & Shi, Y. (2018). Large off-nadir scan angle of airborne LiDAR can severely affect the estimates of forest structure metrics. *ISPRS Journal of Photogrammetry and Remote Sensing*, *136*, 13–25. https://doi.org/10.1016/j.isprsjprs.2017.12.004

Liu, S., Brandt, M., Nord-Larsen, T., Chave, J., Reiner, F., Lang, N., et al. (2023). The overlooked contribution of trees outside forests to tree cover and woody biomass across Europe. *Science Advances*, *9*(37), eadh4097. https://doi.org/10.1126/sciadv.adh4097

Liu, X., Moudrý, V., Schuldt, B., & Forkel, M. (2025). GEDI reveals decline in overstorey and increase in understorey canopy cover of protected forests in Central Europe since 2019. *Forest Ecology and Management*, *597*, 123155. https://doi.org/10.1016/j.foreco.2025.123155

Lovell, J. L., Jupp, D. L. B., Newnham, G. J., Coops, N. C., & Culvenor, D. S. (2005). Simulation study for finding optimal LiDAR acquisition parameters for forest height retrieval. *Forest Ecology and Management*, *214*(1–3), 398–412. https://doi.org/10.1016/j.foreco.2004.07.077

Lowe, C. J., McGrath, C. N., Hancock, S., Davenport, I., Todd, S., Hansen, J., et al. (2024). Spacecraft and optics design considerations for a spaceborne LiDAR mission with spatially continuous global coverage. *Acta Astronautica*, *214*, 809–816. https://doi.org/10.1016/j.actaastro.2023.10.042

Magruder, L., Neumann, T., & Kurtz, N. (2021). ICESat-2 early mission synopsis and observatory performance. *Earth and Space Science*, *8*(5), e2020EA001555. https://doi.org/10.1029/2020ea001555

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. https://doi.org/10.1002/rse2.330

Markonis, Y., Vargas Godoy, M. R., Pradhan, R. K., Pratap, S., Thomson, J. R., Hanel, M., et al. (2024). Spatial partitioning of terrestrial precipitation reveals varying dataset agreement across different environments. *Communications Earth & Environment*, *5*(1), 217. https://doi.org/10.1038/s43247-024-01377-9

Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., et al. (2017). The Ice, Cloud, and land Elevation Satellite-2 (ICESat-2): Science requirements, concept, and implementation. *Remote Sensing of Environment*, *190*, 260–273. https://doi.org/10.1016/j.rse.2016.12.029

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. https://doi.org/10.1088/1748-9326/ac583f

Meyer, H., & Pebesma, E. (2021). Predicting into unknown space? Estimating the area of applicability of spatial prediction models. *Methods in Ecology and Evolution*, *12*(9), 1620–1633. https://doi.org/10.1111/2041-210x.13650

Meyer, H., & Pebesma, E. (2022). Machine learning-based global maps of ecological variables and the challenge of assessing them. *Nature Communications*, *13*(1), 2208. https://doi.org/10.1038/s41467-022-29838-9

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. https://doi.org/10.1016/j.srs.2022.100051

Montaghi, A. (2013). Effect of scanning angle on vegetation metrics derived from a nationwide Airborne Laser Scanning acquisition. *Canadian Journal of Remote Sensing*, *39*(sup1), S152–S173. https://doi.org/10.5589/m13-052

Moudrá, L., Barták, V., Moudrý, V., Remelgado, R., Roilo, S., Rocchini, D., et al. (2025). Habitat heterogeneity derived from LiDAR and hyperspectral data in a restored site and its surroundings: Implications for bird guilds and restoration management. *Journal of Applied Ecology*.

Moudrý, V. (2024). Canopy height models of giant mountains national park (2012 and 2022) at 10 m resolution [Dataset]. https://doi.org/10.5281/zenodo.14270020

Moudrý, V., Cord, A. F., Gábor, L., Laurin, G. V., Barták, V., Gdulová, K., et al. (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. https://doi.org/10.1111/ddi.13644

Moudrý, V., Gábor, L., Marselis, S., Pracná, P., Barták, V., Prošek, J., et al. (2024). Comparison of three global canopy height maps and their applicability to biodiversity modeling: Accuracy issues revealed. *Ecosphere*, *15*(10), e70026. https://doi.org/10.1002/ecs2.70026

Moudrý, V., Gdulová, K., Gábor, L., Šárovcová, E., Barták, V., Leroy, F., et al. (2022). Effects of environmental conditions on ICESat-2 terrain and canopy heights retrievals in Central European Mountains. *Remote Sensing of Environment*, *279*, 113112. https://doi.org/10.1016/j.rse.2022.113112

Moudrý, V., Moudrá, L., Barták, V., Bejček, V., Gdulová, K., Hendrychová, M., et al. (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. https://doi.org/10.1016/j.landurbplan.2021.104064

Moudrý, V., Prošek, J., Marselis, S., Marešová, J., Šárovcová, E., Gdulová, K., et al. (2024). How to find accurate terrain and canopy height GEDI footprints in temperate forests and grasslands? *Earth and Space Science*, *11*(10), e2024EA003709. https://doi.org/10.1029/2024ea003709

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. https://doi.org/10.1016/j.rse.2022.112919

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. https://doi.org/10.1029/2021jg006748

Ng, S. K., Sirguey, P., & Redpath, T. (2025). Performance of global canopy height models across varied New Zealand vegetation types. *New Zealand Journal of Forestry Science*, *55*. https://doi.org/10.33494/nzjfs552025x446x

Okyay, U., Telling, J., Glennie, C. L., & Dietrich, W. E. (2019). Airborne LiDAR change detection: An overview of Earth sciences applications. *Earth-Science Reviews*, *198*, 102929. https://doi.org/10.1016/j.earscirev.2019.102929

Pang, S., Li, G., Jiang, X., Chen, Y., Lu, Y., & Lu, D. (2022). Retrieval of forest canopy height in a mountainous region with ICESat-2 ATLAS. *Forest Ecosystems*, *9*, 100046. https://doi.org/10.1016/j.fecs.2022.100046

Pardini, M., Armston, J., Qi, W., Lee, S. K., Tello, M., Cazcarra Bes, V., et al. (2019). Early lessons on combining LiDAR and multi-baseline SAR measurements for forest structure characterization. *Surveys in Geophysics*, *40*(4), 803–837. https://doi.org/10.1007/s10712-019-09553-9

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. https://doi.org/10.3390/rs15225352

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. https://doi.org/10.1016/j.ecoinf.2022.101748

Pauls, J., Zimmer, M., Kelly, U. M., Schwartz, M., Saatchi, S., Ciais, P., et al. (2024). Estimating canopy height at scale. *arXiv preprint arXiv:2406.01076*.

Pauls, J., Zimmer, M., Turan, B., Saatchi, S., Ciais, P., Pokutta, S., & Gieseke, F. (2025). Capturing temporal dynamics in large-scale canopy tree height estimation. *arXiv preprint arXiv:2501.19328*.

Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H., Scholes, R. J., et al. (2013). Essential biodiversity variables. *Science*, *339*(6117), 277–278. https://doi.org/10.1126/science.1229931

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., et al. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, *253*, 112165. https://doi.org/10.1016/j.rse.2020.112165

Pracná, P., Šárovcová, E., Liu, X., Eltner, A., Marešová, J., Gdulová, K., et al. (2025). Towards 90 m resolution digital terrain model combining ICESat-2 and GEDI data: Balancing accuracy and sampling intensity. *Science of Remote Sensing*, *12*, 100293. https://doi.org/10.1016/j.srs.2025.100293

Réjou-Méchain, M., Barbier, N., Couteron, P., Ploton, P., Vincent, G., Herold, M., et al. (2019). Upscaling forest biomass from field to satellite measurements: Sources of errors and ways to reduce them. *Surveys in Geophysics*, *40*(4), 881–911. https://doi.org/10.1007/s10712-019-09532-0

Riofrío, J., White, J. C., Tompalski, P., Coops, N. C., & Wulder, M. A. (2022). Harmonizing multi-temporal airborne laser scanning point clouds to derive periodic annual height increments in temperate mixedwood forests. *Canadian Journal of Forest Research*, *52*(10), 1334–1352. https://doi.org/10.1139/cjfr-2022-0055

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*, *2024*(11), e07377. https://doi.org/10.1111/ecog.07377

Roussel, J. R., Béland, M., Caspersen, J., & Achim, A. (2018). A mathematical framework to describe the effect of beam incidence angle on metrics derived from airborne LiDAR: The case of forest canopies approaching turbid medium behaviour. *Remote Sensing of Environment*, *209*, 824–834. https://doi.org/10.1016/j.rse.2017.12.006

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. https://doi.org/10.1016/j.rse.2017.05.032

Roy, D. P., Wulder, M. A., Gorelick, N., Hansen, M., Healey, S., Hostert, P., et al. (2026). The next Landsat: Mission turning point? *Remote Sensing of Environment*, *332*, 115087. https://doi.org/10.1016/j.rse.2025.115087

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. https://doi.org/10.3390/f5050936

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). https://doi.org/10.1029/2005gl024009

Schwartz, M., Ciais, P., De Truchis, A., Chave, J., Ottlé, C., Vega, C., et al. (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. https://doi.org/10.5194/essd-15-4927-2023

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. https://doi.org/10.1016/j.foreco.2023.121238

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 and Remote Sensing*, *60*(1), 2260637. https://doi.org/10.1080/15481603.2023.2260637

Shi, Y., Wang, J., & Kissling, W. D. (2025). Multi-temporal high-resolution data products of ecosystem structure derived from country-wide airborne laser scanning surveys of the Netherlands. *Earth System Science Data*, *17*(7), 3641–3677. https://doi.org/10.5194/essd-17-3641-2025

Silva, C. A., Duncanson, L., Hancock, S., Neuenschwander, A., Thomas, N., Hofton, M., et al. (2021). Fusing simulated GEDI, ICESat-2 and NISAR data for regional aboveground biomass mapping. *Remote Sensing of Environment*, *253*, 112234. https://doi.org/10.1016/j.rse.2020.112234

Simard, M., Pinto, N., Fisher, J. B., & Baccini, A. (2011). Mapping forest canopy height globally with spaceborne lidar. *Journal of Geophysical Research*, *116*(G4), G04021. https://doi.org/10.1029/2011jg001708

Skidmore, A. K., Coops, N. C., Neinavaz, E., Ali, A., Schaepman, M. E., Paganini, M., et al. (2021). Priority list of biodiversity metrics to observe from space. *Nature Ecology & Evolution*, *5*(7), 896–906. https://doi.org/10.1038/s41559-021-01451-x

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. https://doi.org/10.1016/j.foreco.2022.120343

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. https://doi.org/10.1111/ele.12277

Stereńczak, K., Lisańczuk, M., & Erfanifard, Y. (2018). Delineation of homogeneous forest patches using combination of field measurements and LiDAR point clouds as a reliable reference for evaluation of low resolution global satellite data. *Forest Ecosystems*, *5*(1), 1. https://doi.org/10.1186/s40663-017-0128-5

Stoker, J., & Miller, B. (2022). The accuracy and consistency of 3d elevation program data: A systematic analysis. *Remote Sensing*, *14*(4), 940. https://doi.org/10.3390/rs14040940

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.

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. https://doi.org/10.1007/s10980-023-01597-y
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. https://doi.org/10.1016/j.rse.2023.113571
Tang, L., Shao, G., & Groffman, P. M. (2024). Urban trees: How to maximize their benefits for humans and the environment. *Nature*, *626*(7998), 261. https://doi.org/10.1038/d41586-024-00300-8
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. https://doi.org/10.1046/j.0305-0270.2003.00994.x
Toivonen, J., Kangas, A., Maltamo, M., Kukkonen, M., & Packalen, P. (2023). Assessing biodiversity using forest structure indicators based on airborne laser scanning data. *Forest Ecology and Management*, *546*, 121376. https://doi.org/10.1016/j.foreco.2023.121376
Tolan, J., Yang, H. I., Nosarzewski, B., Couairon, G., Vo, H. V., Brandt, J., et al. (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. https://doi.org/10.1016/j.rse.2023.113888
Torresani, M., Rocchini, D., Sonnenschein, R., Zebisch, M., Hauffe, H. C., Heym, M., et al. (2020). Height variation hypothesis: A new approach for estimating forest species diversity with CHM LiDAR data. *Ecological Indicators*, *117*, 106520. https://doi.org/10.1016/j.ecolind.2020.106520
Turubanova, S., Potapov, P., Hansen, M. C., Li, X., Tyukavina, A., Pickens, A. H., et al. (2023). Tree canopy extent and height change in Europe, 2001–2021, quantified using Landsat data archive. *Remote Sensing of Environment*, *298*, 113797. https://doi.org/10.1016/j.rse.2023.113797
United Nations. (2021). System of environmental-economic accounting—Ecosystem accounting (SEEA EA). In *White cover publication, pre-edited text subject to official editing*. Retrieved from 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.
Urbazaev, M., Hess, L. L., Hancock, S., Sato, L. Y., Ometto, J. P., Thiel, C., et al. (2022). Assessment of terrain elevation estimates from ICESat-2 and GEDI spaceborne LiDAR missions across different land cover and forest types. *Science of Remote Sensing*, *6*, 100067. https://doi.org/10.1016/j.srs.2022.100067
USGS. (2024). *3DEP LiDAR base specification 2024 Rev. A*. U.S. Geological Survey. Retrieved from https://www.usgs.gov/3DEP/lidarspec
Vaglio Laurin, G., Zabeo, C., Giuliarelli, D., Tesfamariam, B. G., Cotrina-Sanchez, A., Valentini, R., et al. (2025). Monitoring habitat diversity with PRISMA hyperspectral and lidar-derived data in Natura 2000 sites: Case study from a Mediterranean forest. *Ecological Indicators*, *172*, 113254. https://doi.org/10.1016/j.ecolind.2025.113254
Valbuena, R., O'Connor, B., Zellweger, F., Simonson, W., Vihervaara, P., Maltamo, M., et al. (2020). Standardizing ecosystem morphological traits from 3D information sources. *Trends in Ecology & Evolution*, *35*(8), 656–667. https://doi.org/10.1016/j.tree.2020.03.006
van Lier, O. R., Luther, J. E., White, J. C., Fournier, R. A., & Côté, J. F. (2022). Effect of scan angle on ALS metrics and area-based predictions of forest attributes for balsam fir dominated stands. *Forestry*, *95*(1), 49–72. https://doi.org/10.1093/forestry/cpab029
Velikova, M., Fernandez-Diaz, J., & Glennie, C. (2024). ICESat-2 noise filtering using a point cloud neural network. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *11*, 100053. https://doi.org/10.1016/j.ophoto.2023.100053
Vogeler, J. C., Fekety, P. A., Elliott, L., Swayze, N. C., Filippelli, S. K., Barry, B., et al. (2023). Evaluating GEDI data fusions for continuous characterizations of forest wildlife habitat. *Frontiers in Remote Sensing*, *4*, 1196554. https://doi.org/10.3389/frsen.2023.1196554
Wagner, F. H., Dalagnol, R., Carter, G., Hirye, M. C. M., Gill, S., Sagang Takougoum, L. B., et al. (2025). Wall-to-wall Amazon forest height mapping with Planet NICFI, aerial LiDAR, and a U-Net regression model. *Remote Sensing in Ecology and Conservation*, rse2.70041. https://doi.org/10.1002/rse2.70041
Wang, J., Choi, D. H., LaRue, E., Atkins, J. W., Foster, J. R., Matthes, J. H., et al. (2024). NEON-SD: A 30-m structural diversity product derived from the NEON discrete-return LiDAR point cloud. *Scientific Data*, *11*(1), 1174. https://doi.org/10.1038/s41597-024-04018-0
Weber, M., Beneke, C., & Wheeler, C. (2025). Unified deep learning model for global prediction of aboveground biomass, canopy height, and cover from high-resolution, multi-sensor satellite imagery. *Remote Sensing*, *17*(9), 1594. https://doi.org/10.3390/rs17091594
White, J. C., Penner, M., & Woods, M. (2021). Assessing single photon LiDAR for operational implementation of an enhanced forest inventory in diverse mixedwood forests. *The Forestry Chronicle*, *97*(1), 78–96. https://doi.org/10.5558/tfc2021-009
White, J. C., Tompalski, P., Bater, C. W., Wulder, M. A., Fortin, M., Hennigar, C., et al. (2025). Enhanced forest inventories in Canada: Implementation, status, and research needs. *Canadian Journal of Forest Research*, *55*, 1–37. https://doi.org/10.1139/cjfr-2024-0255
Wildermuth, B., Dönges, C., Matevski, D., Penanhoat, A., Seifert, C. L., Seidel, D., et al. (2023). Tree species identity, canopy structure and prey availability differentially affect canopy spider diversity and trophic composition. *Oecologia*, *203*(1), 37–51. https://doi.org/10.1007/s00442-023-05447-1
Wilkes, P., Jones, S. D., Suarez, L., Haywood, A., Woodgate, W., Soto-Berelov, M., et al. (2015). Understanding the effects of ALS pulse density for metric retrieval across diverse forest types. *Photogrammetric Engineering & Remote Sensing*, *81*(8), 625–635. https://doi.org/10.14358/pers.81.8.625
Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., et al. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*, *3*(1), 1–9. https://doi.org/10.1038/sdata.2016.18
Wulder, M. A., White, J. C., Nelson, R. F., Næsset, E., Ørka, H. O., Coops, N. C., et al. (2012). Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment*, *121*, 196–209. https://doi.org/10.1016/j.rse.2012.02.001
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. https://doi.org/10.1016/j.rse.2024.114446
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*, *10*(6), 725–742. https://doi.org/10.1002/rse2.398
Zlinszky, A., Schroiff, A., Kania, A., Deák, B., Mücke, W., Vári, Á., et al. (2014). Categorizing grassland vegetation with full-waveform airborne laser scanning: A feasibility study for detecting Natura 2000 habitat types. *Remote Sensing*, *6*(9), 8056–8087. https://doi.org/10.3390/rs6098056