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REVIEWS

Assessing the Accuracy of Global Canopy Height Models: A Comprehensive Review

Evaluación de la Exactitud de Modelos Globales de Altura del Dosel: Una revisión exhaustiva

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SUMMARY

Accurate measurements of canopy heights play a pivotal role in estimating vegetation biomass. The Advanced Topographic Laser Altimeter System (ATLAS), and the Global Ecosystem Dynamics Investigation (GEDI) have significantly improved LiDAR capability for three-dimensional mapping. Global canopy height maps were released at medium to very high spatial resolutions: Land and Vegetation Height (ATLAS-ATL08 product), Global Forest Canopy Height Map (GFCH), the High-Resolution Canopy Height Model of the Earth (HRCH), and Global Map of Tree Canopy Height (GMTCH). This study aimed to provide a review of the accuracy assessment results of the recent global canopy height maps, by comparing them with independent airborne laser scanning (ALS) data. According to the findings, global canopy height models were mainly validated in boreal and temperate forests, primarily in North America, Europe, and Oceania. ATL08 canopy heights underestimated canopy heights in most cases, reporting mean errors (MEs) less than -2.3 m, and root mean square errors (RMSEs) ranging from 2.9 m to 7 m. GFCH showed larger negative vertical offsets with MEs ranging from -3.8 m to -14 m (RMSEs 9 m - 18 m). On the other hand, HRCH tended to overestimate (MEs 1,7 m - 6.0 m, RMSEs 8 m - 11 m) most forested areas. GMTCH consistently underestimated the height of all canopies with MEs ranging from -7 m to -12 m (RMSEs 10 m - 17 m). Recommendations are provided to enhance the global availability of independent ALS data, and potential application for the maps are recognized.

Keywords: spaceborne LiDAR, ALS surveys, artificial intelligence, open-access databases.

RESUMEN

Las mediciones precisas de la altura del dosel forestal desempeñan un rol fundamental en la estimación de la biomasa vegetal. El Advanced Topographic Laser Altimeter System (ATLAS), y el Global Ecosystem Dynamics Investigation (GEDI) han mejorado significativamente la capacidad de los datos LiDAR para el mapeo tridimensional. Se publicaron Mapas globales de altura del dosel de media a muy alta resolución espacial: Altura del Suelo y Vegetación (producto ATLAS-ATL08), Mapa Global de Altura del Dosel Forestal (GFCH), Modelo de Alta Resolución de Altura del Dosel Forestal de la Tierra (HRCH) y el mapa global de altura de árboles (GMTCH). El objetivo del estudio fue proporcionar una revisión del análisis de exactitud de los recientes mapas globales de altura del dosel, comparándolos con datos independientes de LiDAR aerotransportado (ALS). De acuerdo a los resultados, los modelos globales de altura del dosel fueron principalmente validados en bosques boreales y templados de Nordamérica, Europa y Oceanía. Las alturas del dosel de ATL08 subestiman la altura en la mayoría de los casos, reportando errores medios (MEs) menores a -2.3 m y errores cuadráticos medios (RMSs) en un rango entre 2.9 m y 7 m. GFHM mostró desplazamiento vertical negativo más alto con MEs en el rango de -3,8 m a -14 m (RMSEs 9 m - 18 m). Por otro lado, HRCH tendió a sobreestimar (MEs 1.7 m - 6.0 m, RMSEs 8 m - 11 m) la mayoría de las áreas con bosques. GMTCH subestimó consistentemente la altura de todo el dosel con MEs en el rango de -7 m a -12 m (RMSEs 10 m - 17 m). Se realizan recomendaciones para mejorar la disponibilidad global de datos independientes ALS, y se identifican potencial utilización de los mapas.

Palabras clave: LiDAR espacial, relevamientos LiDAR aerotransportado, inteligencia artificial, base de datos de acceso abierto.

INTRODUCTION

Accurate measurements of canopy heights play a pivotal role in estimating vegetation biomass and carbon stocks. Allometric equations are used to estimate forest biomass in non-destructive approaches (Yang et al., 2022). Power relationship exists between most allometric models and diameter at breast height (DBH) which is strongly related to height. Light Detection and Ranging (LIDAR) technology has become a dominant data collection tool for measuring vertical forest structures and for estimating aboveground biomass (Borsah et al., 2023). Rapid and accurate retrieval of vegetation canopy surfaces and the underlying topography is also essential for gaining a deeper understanding of terrestrial ecosystem functions and services (Friedlingstein et al., 2020). LiDAR has emerged as a reliable technology for characterizing surface topography and vertical canopy structure as it can provide detailed and precise three-dimensional information about surface objects (Narine et al., 2019). Monitoring terrain elevation and vertical canopy structure on a large spatial scale is best achieved through spaceborne LiDAR technology (Xi et al., 2022). Due to their high data acquisition costs, neither terrestrial nor airborne LiDARs are suitable for large-scale observations of terrestrial ecosystems (Lu et al., 2024).

The launched ICESat-2 equipped with the Advanced Topographic Laser Altimeter System (ATLAS) in 2018, and the Global Ecosystem Dynamics Investigation (GEDI) installed aboard the International Space Station (ISS) as of 2019 has significantly improved LiDAR capability for constructing detailed three-dimensional mapping (Wang et al., 2024). Based on these sensors, many researchers in the last decade have built statistical (Potapov et al., 2021) or machine learning models (Lang et al., 2023) to retrieve canopy height at regional (Duncanson et al., 2020, Dorado-Roda et al., 2021, Liu et al., 2022, Liu & Wang, 2022) and global scales (Potapov et al., 2021, Lang et al., 2023) mainly by integration with optical spaceborne data. Recently, statewide (Kacic et al., 2023, Schwartz et al., 2024, Alvites et al., 2025) and global canopy height maps (Tolan et al., 2024) were released at medium to very high spatial resolutions, using artificial intelligence (AI) modeling that integrate multi-stream remote sensing data. The models utilize mainly GEDI measurements, but also airborne laser scanning (ALS) datasets (Tolan et al., 2024), along with spatially continuous satellite optical and/or SAR datasets.

Continuous pixel by pixel spatial coverage of data, i.e., wall-to-wall data, on tree height and canopy structure is used to estimate aboveground woody biomass (Duncanson et al., 2022). Only if the accuracy and uncertainty of forest parameters maps are comprehensively assessed and quantified will they meet the needs of the user communities (Duncanson et al., 2019, Labrière et al., 2023). According to the requirements of the German National Forest Inventory, the error tolerance for tree height measurement is set at ±5% for coniferous trees and ±10% for deciduous trees, with a maximum error cut-off of ±2 m for both tree types (Riedel et al., 2020). The accuracy requirements are higher, with a maximum acceptable error below 1.5 meters when height estimations support forest management decisions (Fassnacht et al., 2025).

This study aims to provide a review of the accuracy assessment results of the recent global canopy height maps, by comparing them with independent ALS data. The work highlights the limitations and potential applications of the global canopy height models, and offers recommendations to enhance the availability of ALS data for accuracy assessment.

METHODS

Datasets. The Ice, Cloud, and land Elevation Satellite (ICESat) pioneered the use of spaceborne LiDAR technology in measuring Earth's surface topography and vegetation canopy height. The sole instrument on ICESat was the Geoscience Laser Altimeter System (GLAS), a space-based LiDAR. The GLAS lasers emitted infrared and visible laser pulses and produced a series of approximately 70 m diameter laser spots that were separated by nearly 170 m along the spacecraft's ground track (Simard et al., 2011). ICESat concluded its mission in 2009. Since then, a new generation of LiDAR instruments has been currently collecting height measurements for sample locations from space across the Earth's surface.

Advanced Topographic Laser Altimeter System (ATLAS). The satellite ICESat-2 was launched in 2018 and equipped with the ATLAS that adopts multi-beam micro-pulse photon counting technology and is based on single-photon detection technology. Single-photon sensitive LiDAR systems are able to detect individual photons from the reflected pulse as opposed to linear-mode instruments that require thousands of photons in order to detect a return. This allows the laser to be operated with lower energy pulses and higher repetition rates (Neumann et al., 2019).

The ATLAS instrument transmits three pairs of laser beams at a wavelength of 532 nm. Each pair consists of one strong-energy beam and one weak-energy beam, with an energy ratio of approximately 4:1. The strong beams are designed to measure low-reflectivity surfaces, such as oceans and vegetation, where a higher signal-to-noise ratio is necessary. In contrast, the weak beams are optimized for high-reflectivity surfaces, such as ice and snow, where the strong beams could potentially saturate the detector (Neumann et al., 2019). The beam configuration results in three pairs of parallel profiles spaced by 3.3 km (in-between pairs spacing of 90 m) on the ground. ICESat-2 has an orbital repeat cycle of 91 days, although the laser pointing direction is slightly shifted off-nadir at every repeat cycle over land to enhance the spatial distribution of measurements in the mid-latitudes (Neuenschwander & Pitts, 2019). Each ATLAS beam results in footprints of approximately 11 m in diameter at the ground level spaced by 70 cm in the along-ground track direction (Magruder et al., 2020, Neuenschwander et al., 2020). However, the number of photons that return to the telescope depends on surface reflectivity and cloud cover. As such, the spatial resolution of signal photons varies. The geolocation accuracy of ATLAS pulses is expected to be well within the mission requirement of 6.5 m (Magruder et al., 2020). Since ICESat-2 has a near-polar orbit, it has dense footprint coverage in high latitude regions (Neuenschwander et al., 2020).

Although ICESat-2 was not designed primarily for characterizing vegetation structure and biomass, a land and vegetation height product is generated that estimates forest canopy heights globally. ICESat-2 provides data products at four different levels. ATL08 (Land and Vegetation Height) data is a product that records photon classification as well as estimated terrain height and canopy height arranged in the 100 m segments along the ground track (National Snow and Ice Data Center, 2018; Neuenschwander et al., 2023).

Global Ecosystem Dynamics Investigation (GEDI). The GEDI was specifically designed to observe vertical structure and biomass of vegetation on the Earth's surface. GEDI is operated at an orbital altitude of approximately 400 km onboard the ISS. It has been collecting data since April 2019. GEDI emits pulses with a long near-infrared wavelength of 1064 nm and collects data over eight parallel ground tracks. Footprints have a 25 m diameter and are spaced every 60 meters (along-track) and 600 meters (across-track). Its across-track width is about 4.2 km, meaning it scans a swath 4.2 km wide from side to side as it moves forward along the ISS orbit (Hofton & Blair, 2019, Dubayah et al., 2020). Unlike ATLAS, GEDI is a full-waveform sensor, which means that the intensity of returned energy, after reflection from the Earth's surface, is recorded as a function of time (Hancock et al., 2019).

For each footprint, the LiDAR waveform backscattered is recorded and processed to provide GEDI data products at footprint level. For example, GEDI L1B provides geolocated full waveform LiDAR data, capturing the energy returned from Earth's surface and vegetation, including elevation and waveform shape. GEDI L2A builds on L1B by processing the waveforms to derive vegetation structure metrics such as Relative Heights (RHx, at the xth percentile), canopy height, ground elevation, multiple algorithm settings, and geolocation data (Tang et al., 2019). RHx are derived from the waveform and represent the vertical position below which x% of the total cumulative energy of the waveform has been returned. RH100 indicates the top-of-canopy return, 100% of energy returned, and approximates the maximum canopy height. The ISS's low orbit, size and shape results in increased mechanical vibrations and greater variations in orientation and altitude than traditional Earth Observation satellites. Consequently, the horizontal position precision of GEDI footprints was expected at 10 m after calibration (Dubayah et al., 2020). For GEDI products' first version (v1), released before in-flight calibration, the mean 1 σ horizontal geolocation error reached 23.8 m. After a calibration process accounting for geolocation biases, a second data (v2) version was released in April 2021 with a positioning error estimated at 10.2 m, with a final targeted accuracy of eight m (Beck et al., 2021). GEDI initially planned to last two years and collected four years of data from 2019 to 2023. After a period of hibernation on the ISS from March 2023 to April 2024, GEDI has returned to its original spot on the ISS to begin collecting data through 2030 and is expected to cover, at most, 4% of the land surface (GEDI, 2024).

The GEDI footprint-level products represent a point sample of a limited portion of the land area, which restricts the resolution of gridded mission products. In contrast, satellite missions such as Landsat or Sentinel-2, deliver freely accessible archives of optical images and offer longer-term global coverage at high spatial and temporal resolution. Sensor fusion between GEDI and multispectral optical imagery has the potential to overcome the limitations of each individual data source. Based on this perspective, recently, global canopy height maps have been released.

Global forest canopy height map (GFCH). Potapov et al. (2021) employed Shuttle Radar Topography Mission (SRTM) and global Landsat analysis-ready data to extrapolate GEDI footprint-level forest canopy height measurements, creating a 30 m spatial resolution global forest canopy height map (GFCH) for the year 2019 (University of Maryland, 2019).

High-Resolution Canopy Height Model of the Earth (HRCH). Lang et al. (2023) have developed a deep learning method by fusing GEDI observations (RH98, the relative height at which 98% of the energy has been returned) with Sentinel-2 images to produce a global map of canopy-top height, with 10 m ground sampling distance for the year 2020. Furthermore, Lang et al. (2023) designed a method to quantify predictive uncertainty for the HRCH, taking into account, on the one hand, the inevitable noise in the input data and, on the other hand, the uncertainty of the model parameters resulting from the lack of reference data for certain conditions. The generated HRCH model includes thus quantitative explicit uncertainty estimates and can be used to identify erroneous estimates (Lang et al., 2022).

By employing a more sophisticated method involving AI and multi-source remote sensing, Tolan et al. (2024) developed a very high resolution global canopy height model.

Global Map of Tree Canopy Height (GMTCH). Meta (2025) (https://www.meta.com) and World Resources Institute (2025) released the Global Map of Tree Canopy Height (GMTCH) in 2024 at a 1 meter resolution. Vision Transformer (ViT) was pretrained in a self-supervised fashion using 18 million WorldView-2, -3, and Quickbird II images from 2017 to 2020 and a dense prediction decoder was trained against aerial LiDAR maps (Tolan et al., 2024). To mitigate the effect of the limited geographic distribution of available ALS data, the developers of GMTCH employed a second regression network trained on RH95 GEDI data to rescale the ALS network outputs (Tolan et al., 2024). GMTCH should capture any vegetation that is higher than one meter and with a canopy diameter of more than three meters. Tolan et al. (2024) did not provide information regarding the estimation of the predictive uncertainty.

A systematic review was conducted to identify and select the most recent literature sources based on the statement of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021). The outcomes were limited to i) peer-reviewed scientific publications over the last 5 years, ii) regional studies assessing the accuracy of global canopy height covers (ATL08, GFCH, HRCH, GMTCH), by comparison to independent ALS data, iii) scientific publications that are written in English, German or Spanish. Regional studies in this context involve comparisons with independent ALS data from forests across at least two countries, or over regions exceeding 1,000 km^2 when considering ALS data from forests within a single country.

The following statistics were mainly surveyed;

$$ME = \frac{1}{n}\sum_{i=1}^{n}(h_{GCHMi} - h_{REFi}) \quad [1]$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|h_{GCHMi} - h_{REFi}| \quad [2]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(h_{GCHMi} - h_{REFi})^2} \quad [3]$$

where ME is mean error, MAE is mean absolute error, RMSE is root mean squared error, ^{h}GCHM*i* is the *i*th canopy height from the global canopy height map, ^{h}REF*i* is the corresponding canopy height from the independent ALS data, and *n* is the number of samples.

The conceptual processing used for LIDAR-independent data involves that ALS datasets as point cloud format are rasterized along a high-resolution grid, and used to estimate canopy height by subtracting the lowest quantile heights (ground surface) from the heights of the highest quantiles (top of canopy). This allows the computation of “true” height maps. A positive mean error (ME) indicates that the canopy height model (CHM) overestimates heights on average, while a negative ME indicates underestimation. ME can mask the true magnitude of individual errors due to cancellation of positive and negative values, so it does not reflect the magnitude of errors well. MAE provides the average magnitude of the errors, regardless of their direction (positive or negative) offering a clearer measure of overall accuracy. RMSE quantifies the typical error magnitude and is more sensitive to outliers or large deviations than MAE.

RESULTS

A lack of systematic information regarding the parameters reported on the accuracy of the independent ALS data was observed. The independent ALS data were mostly available as point cloud format (e.g., Moudrý et al., 2024; Rai et al., 2024). On the other hand, high-resolution canopy height models derived from small-footprint ALS campaigns were utilized. This is, for example, the study conducted by Lang et al. (2023), who referenced Liu et al. (2023) to obtain ALS information. Only a few authors, such as Queinnec et al. (2021), reported the vertical accuracy of the independent ALS data in both areas, unobstructed by vegetation, and those with vegetation. In this case, the specified value of vertical accuracy in vegetated areas was included in Table 1.

According to Table 1, independent ALS data were generated with a point density between 0.5 and 55 points m². Vertical errors of the independent ALS data were mostly below 0.36 m.

Due to the temporal mismatch between satellite data used for generating global canopy heights and independent ALS data, researchers verified whether the differences in canopy height were caused by selective logging activities (Rai et al., 2024) or wildfires (Lang et al., 2023).

Several studies have already contributed to the validation of ATL08 accuracy, and reported higher accuracies for terrain than for canopy height estimations. Neuenschwander et al. (2020) quantified the accuracy of terrain and canopy height from ATL08 using ALS data collected in southern Finland. Neuenschwander *et al*. (2020) reported that canopy height estimations were dependent on the strength of the ATLAS beam, indicating that the strong beam consistently provided better estimates than the weak beam. ATL08 incorporating data acquired during the summer months had the lowest canopy height errors (ME ≈ 0.5 m, RMSE ≈ 2.5 m).

In snow conditions, the canopy height errors were larger (ME ≈ 1.1 m, RMSE ≈ 2.7 m). The mean error for all beams was estimated to be 3.05 m (Neuenschwander et al., 2020). For ATLAS data acquired in all seasons and lighting conditions, and when only the results from the strong beam are taken into consideration, Neuenschwander et al. (2020) assessed a mean error of -0.86 m in forest land cover classes. They also concluded that canopy heights were most accurate when canopy cover ranged from 40% to 85%.

The study of Queinnec et al. (2021) contributes to the characterization of ATL08 data for vegetation structure retrieval by comparing it to airborne ALS data acquired over a range of Canada’s boreal maturity forest-classes. According to Queinnec et al. (2021), ATLAS photons returned from the top of the canopy underestimated canopy height by an average of 2.3 m overall and corresponded most strongly to the 90th percentile of coincident airborne LiDAR returns (RMSE 2.9 m). The lowest average under-

Table 1. Accuracy assessment of global canopy height models based on independent ALS data, ALS surveying parameters, main forest types, and categorization into continents according to the location of the independent data.

Evaluación de la exactitud de modelos globales de altura del dosel en base a datos independientes de LiDAR aerotransportado, parámetros de los relevamientos con LiDAR aerotransportado, principales tipos de bosques y categorización en continentes según localización de los datos independientes.

GCHM	Independent ALS data/ ppms / vertical height error (m)	Accuracy Assessment (m)	Main forest types	Author	C
ATL08	Optech ALTM Gemini / 0.5-1 / < 0.15	ME: -0.9	Boreal zone, mix of broadleaf and coniferous forest.	Neuenschwander et al. (2020)	Eu
	SPL100 / 40 / 1.9	ME: -2.3 RMSE: 2.9	Boreal zone, mix of broadleaf and coniferous forest.	Queinnec et al. (2021)	Na
	Riegl LMSQ680i / 4-55 / ≤ 0.15	ME: -1.2 to -2.1 RMSE: 5.1 to 7	Temperate broadleaf forest. mixed coniferous forest.	Moudrý et al. (2022)	Eu
	Leica ALS70-80, Riegl VQ1560i-ii / 2-2.7 / 0.1	ME: -0.5 to -1.9 RMSE: 3.6 to 4.9	Temperate decidous forest, evergreen and mixed forest.	Rai et al. (2024)	Na
GFCH	G-LiHT, ALTM 3100, Riegl LMS-Q560 / 1- 10 / <0.35	ME: -3.8 MAE: 6.4 RMSE: 9.1	Temperate (coniferous, broadleaf), tropical forest.	Potapov et al. (2021)	Na Ao Af
	(1) LVIS and other LiDAR sensors / ≈5 / <0.18	ME: -4.5 MAE: 6.7 RMSE: 9.1	(2) Temperate (coniferous, broadleaf), mediterranean forest, tropical (coniferous, broadleaf), tropical dry broadleaf forest.	Lang et al. (2023)	Na Eu Af
	(3) Optech Galaxy T2000 / 8 / < 0.3, Optech ALTM Gemini / 5-9 / 0.1-0.5	ME: -4 to -14 RMSE: 10 to 18	(4) Temperate coniferous, broadleaf, mixed conifer forests and plantation forests.	Moudrý et al. (2024)	Na Eu Ao
HRCH	(1)	ME: 1.7 MAE: 6.3 RMSE: 7.9	(2)	Lang et al. (2023)	Na Eu Af
	(3)	ME: 4 to 6 RMSE: 9 to 11	(4)	Moudrý et al. (2024)	Na Eu Ao
GMTCH	Optech Gemini, Galaxi and Riegl Q780 / 5-30 / <0.15, Leica ALS50 / ≈10 / <0.36	ME: 0.6 MAE: 2.8 RMSE: 4.4	Temperate coniferous and broadleaf forests, mixed conifer forests. Tropical forest.	Tolan et al. (2024)	Na Sa
	(3)	ME: -7 to -12 RMSE: 10 to 17	(4)	Moudrý et al. (2024)	Na Eu Ao

GCHM: Global canopy height models, ppms: points per square meter. ATL08: Land and Vegetation Height, GFCH: Global Forest Canopy Height map, HRCH: High-Resolution Canopy Height Model, GMTCH: Global Map of Tree Canopy Height, ME: Mean error, MAE: Mean absolute error, RMSE: Root mean square error, C: Continent, Na: North America includes Middle America (comprising the Caribbean, Central America, and Mexico) and Northern America, Sa: South America, Eu: Europe, As: Asia, Ao: Australia/Oceania, Af: Africa.

estimation was observed in homogeneous stands that were relatively simple, single-layered with a single dominant species (RMSE 2.5 m). Queinnec et al. (2021) also observed the least agreement of ATL08 and forest structural metrics in over-mature stands with complex structures and greater variability in canopy heights (RMSE 3.5 m).

Moudrý et al. (2022) evaluated the vertical accuracy of ATL08 terrain and canopy height in three Central European mountain ranges and their surrounding areas situated in Germany, Czech Republic, and Poland by comparing them with the digital terrain model and canopy height model derived from ALS data. Their results indicated that in summer canopy height in broadleaf/mixed as well as coniferous forests are underestimated on average by 2.1 m and 1.2 m, respectively. In winter, however, the underestimation increased to 8.5 m and 5.7 m, respectively. Moudrý *et al*. (2022) found that the overall RMSEs were 7.03 m and 5.09 m for the weak and strong beams, respectively.

Also, Rai et al. (2024) assessed the performance of ATL08 canopy height metrics by evaluating their agreements with ALS-derived canopy height datasets in a region of Mississippi, United States. They found that ATL08 canopy heights underestimated ALS canopy heights across forest types with the smallest underestimation in evergreen (ME -0.47 m, RMSE 3.63 m) and largest in deciduous forest (ME -1.92 m and RMSE 4.95 m). ATL08 underestimated 1.36 m (RMSE 4.35 m) the independent ALS data in mixed forest. ATL08 seemed to overestimate canopy heights for height classes below 10 m. When canopy cover was greater than 65% and up to 90%, a best agreement between ATL08 and ALS height metrics was by Rai et al. (2024) observed.

Potapov et al. (2021) compared GFCH with independent ALS data collected from the USA, Mexico, the Democratic Republic of the Congo, and Australia. They found that GFCH underestimated forest height (ME -3.8 m) and revealed an RMSE of 9.07 m. The error distribution suggests that the mean underestimation was greater within short (3 m) and tall forests (above 21 m height). The errors in GFCH reported by Potapov et al. (2021) are greater than those found in the ATL08 accuracy assessments of the aforementioned studies.

Lang et al. (2023) compared the GFCH and HRCH with independent ALS data corresponding to 11 country areas mainly in North and Central America and Europe, and Gabon covering a diverse range of vegetation heights and biomes. Lang et al. (2023) found that GFCH had an RMSE of 9.1 m, an MAE of 6.7 m, and a ME of -4.5 m, and showing similar ME, MAE, and RMSE as validation of GFCH provided by Potapov et al. (2021). Moudrý et al. (2024) assessed the accuracy of three modeled global canopy height maps (GFCH, HRCH, and GMTCH) using ALS data obtained in Switzerland, New Zealand, and California. Regarding GFCH, they reported that MEs varied from -4.0 m to -14.0 m, and RMSE values ranged from 10 m to 18 m.

By assessing HRCH, Lang et al. (2023) reported an RMSE of 7.9 m, an MAE of 6.3 m, and a ME of 1.7 m compared to ALS data. Moudrý et al. (2024) determined higher errors, with RMSE varying from 9 m to 11 m, while ME positively ranged from 4 m to 6 m.

Tolan et al. (2024) evaluated the Global Map of Tree Canopy Height (GMTCH) performance against various metrics, including an independent validation dataset of ALS available for the USA and Brazil. Tolan et al. (2024) reported that GMTCH produces an average ME of 0.6 m (MAE 2.8 m, RMSE 4.4 m). On the other hand, the accuracy assessment conducted by Moudrý et al. (2024) revealed that GMTCH, when compared with independent ALS data from Switzerland, New Zealand, and California, consistently underestimated the height of all canopies regardless of their height. Moudrý et al. (2024) reported large errors with RMSEs ranging from 10 m to 17 m and MEs spanning from -7 m to -12 m.

DISCUSSION AND CONCLUSIONS

ALS system are valuable to validate canopy height estimations from other sources like satellite data, although it has inherent errors, that can lead to distortions in all three dimensions, which must be considered when using ALS data as independent datasets. These errors can arise from various factors, including sensor limitations, environmental conditions, and data processing techniques. A study by Prieur et al. (2022), indicated the differences of laser beams penetration in thicker canopies by comparing airborne LiDAR sensors with green wavelength (e.g., SPL 100) or infrared (IR) channels (e.g., Riegl 680i). This also affects the terrain modeling. Terrain-induced canopy height differences are mainly determined by the slope gradient and the crown radius. When the laser hit is on the edge of the crown, and is in the upslope direction, the maximum height difference is expected to be observed. Steeper slopes and larger crowns cause the largest differences (Duan et al., 2015). ALS data is also vulnerable to uncertainties depending on the season, under leaf-on or leaf-off forest canopy conditions (Davison et al., 2020).

Independent ALS data used for accuracy assessments were available as ALS-based canopy height maps or point clouds. The advantage of accessing the original data as point clouds, is that researchers can calculate top of canopy over different scenarios of RHx metrics, to provide the closest alternative for comparison to the canopy-top height definition (e.g., RH95, RH98) applied to generate the global canopy height (Rai et al., 2024).

According to Goodbody et al. (2021), ALS data with more than 10 points per square meter can be used to detect individual crowns and terrain features. Based on Table 1, some studies did not meet this benchmark. Concerning the vertical precision of the independent ALS data, this study shows mostly errors below 0.36 m. The reported errors could also contribute to the overall error when analyzing the accuracy of global canopy maps. The major error (1.9 m) indicated by Queinnec et al. (2021) must be taken with caution, as it was determined by comparing SPL100 data with the ground-measured height of the tallest trees.

Table 1 indicates that global canopy height models were most frequently validated in boreal and temperate forests, primarily in North America, Europe, and Oceania, with limited accuracy assessments in tropical forests of Africa and South America. A major challenge in applying spaceborne data to generate global canopy height maps is the relative scarcity of ALS data that is publicly available to the scientific community. This lack can negatively impact the generalizability of models (Schacher et al., 2023). Although ALS data are regularly acquired in various countries, ALS surveys and their metadata are not always easily accessible (Ouaknine et al., 2025). Fogel et al. (2024) highlighted that a crucial step in improving the transparency of product evaluations from global satellite missions, is to systematically organize the parameters of ALS surveys. Important metadata to report includes the flight date, type and model of LiDAR, point density, horizontal and vertical accuracy, as well as whether it refers to vegetated or non-vegetated areas. Additionally, factors such as terrain roughness, phenological condition of the vegetation during the ALS surveys, attributes related to structure attributes (e.g., dominant height, species composition, and density) of the reference sites are essential for enhancing the understanding of accuracy assessment findings (Stereńczak et al., 2020).

ALS provides precise measurements of canopy height but its high cost and logistical requirements make frequent data acquisition impractical (Coops et al., 2021). Consequently, complementary and synergistic information to independent ALS data, derived from terrestrial LiDAR surveys, or UAV-mounted LiDAR, at plot or tree scale, will also require enhanced systematization and accessibility.

Ongoing multiscale efforts aim to fill this gap. GlobALS was developed by a group of international researchers working at the interface between remote sensing and the ecological sciences to establish a worldwide network of ALS data willing to work together to support natural resource and biodiversity monitoring (Stereńczak et al., 2020). Ouaknine et al. (2025) introduced the OpenForest catalog, which consolidates 86 open-access forest datasets, including various spatial scales and types of recordings such as inventories, ground-based, aerial-based data, including ALS surveys, and satellite datasets. The network does not collect data itself but collects metadata and facilitates networking and collaborative research among the end-users and data providers. GlobALS covers test sites in Europe, Asia, and Africa. The network has a structured database about ALS and field information, extending it to metadata related to, among others, biomass expansion factors and terrestrial laser surveys. At regional scale, Keller et al. (2024) created a platform to free access to ALS data covering the Amazon rainforest, Cerrado, and Atlantic rainforest. It is hosted at Embrapa Agricultural Informatics (Embrapa Digital Agriculture, 2016). Fogel et al. (2024) generated Open-Canopy, the first open-access, country-scale benchmark with both very high resolution imagery and ALS-based canopy height maps at 1.5 m spatial resolution across France.

Another important aspect is that accuracy assessments with independent ALS data will require not only the availability of data in the under-surveyed forest regions, but it is also relevant to generate repeat measurements (Atkins et al., 2023), that is, new ALS measurements of canopy structure collected systematically at the same site. In light of the trend that global canopy maps will be periodically updated (Alvites et al., 2025) repeat measurements will enhance the calibration and/ or validation methods of the global maps.

Open-access long-term field plot databases are improving spatial coverage in tropical forests across Africa, Asia and South America, e.g., African Tropical Rainforest Observation Network (AfriTRON, 2020), ForestPlots (2014) and Amazon Forest Inventory Network (RAINFOR, 2025). Collaborative efforts in tropical forest networks to promote and integrate ALS data could serve as a strategy to enhance the global availability of independent validation data.

According to the results of the accuracy assessment presented in the Table 1, ATL08 canopy heights underestimated ALS canopy heights, reporting negative mean errors between -0.5 m and -2.3 m and RMSE < 7 m. Moudrý et al. (2022) and Rai et al. (2024) found that height errors were lower in coniferous forests than in deciduous ones because of the complex structure, and seasonal variability, which reduce accuracy. There was a stronger agreement in canopy heights measured with strong beam at night. This is due to the strong beam having greater penetration and can extract canopy information more accurately. Data acquired at night are less affected by background noise caused by the solar radiation (Rai et al., 2024). ATL08 overestimates tree heights for shorter trees and underestimates the heights of taller (Rai et al., 2024). These findings align with those of Liu et al. (2021), who found that ICESat-2 tend to overestimate canopy height in dwarf shrublands.

Evaluating specific factors is essential for obtaining a deeper understanding when analyzing the results. Undulating terrain conditions with dense forest cover can seriously affect the number of photons reaching the ground and the precision of photon classification, thus further influencing the extraction of digital terrain model (DTM) and canopy height model data (Neuenschwander et al., 2020, Dong et al., 2021). Some previous studies have reported that the RMSE between ICESat-2 DTM and airborne LiDAR DTM can be less than 1 m in flat regions, while the RMSE of forest canopy height can be as high as 4.5-5.5 m in hilly areas, and the major errors are from the low accuracy of DTM (Xing et al., 2020). As terrain slope increases, the accuracy of ICESat-2 DTM becomes worse (Wang et al., 2019). Queinnec et al. (2021) highlight that ATL08 mean canopy height deteriorates with the increasing terrain slope. This finding concurs with the study of Moudrý et al. (2022).

Forest cover also greatly impacts the retrieval accuracy. As forest cover increases, the accuracy of DTM and canopy height derived from ATLAS decreases (Dong et al., 2021). The best accuracy of the canopy height estimation is observed for canopy cover ranging from 40% to 60% (Moudrý et al., 2022). Rai et al. (2024) show that areas with 65% and 90% forest cover had best agreement. Another factor that shows a strong impact on the accuracy is the underestimation of the mean forest canopy height, resulting from the presence of snow on the terrain (Moudrý et al., 2022).

Accuracy assessment of GFCH consistently shows a negative vertical offset for forested areas within a range of -3.8 m to -14 m, while the RMSE values vary from 9 m to 18 m. The errors (ME and RMSE) are larger than those reported for ATL08 data.

The HRCH map reveals a positive vertical offset with ME from 1.7 m to 6.0 m and RMSE values ranging from 8 m to 11 m. Moudrý et al. (2024) report that HRCH overestimates the height of low canopies (up to 10 m high) on average by 10 m and overestimates the height of tall canopies (taller than 30 m).

Comparing GFCH and HRCH, Lang et al. (2023) assess that GFCH map underestimates the independent ALS data in all regions, while HRCH mostly tends to overestimate it. The strongest differences are observed in regions with a high average canopy height (> 32 m, e.g., at locations in Gabon), where the GFCH map has MEs ranging from -5.9 m to -7.9 m, and HRCH yields MEs of -4.8 m to 1.5 m. Qualitatively, the HRCH model captures structure within high vegetation, where GFCH saturates (Lang et al., 2023).

Considering that the global GFCH and the HRCH were developed by integrating the GEDI data with spaceborne passive optical images, it is highlighted that also slope, aspect, land cover, density of canopy cover, and the selected dataset according to plant growing season have shown to influence GEDI estimations (Pourrahmati et al., 2023, Schleich et al., 2023). With this in mind, some additional considerations need to be made about other sources of error. The observed underestimation of the GFCH compared to the ALS data can be attributed to several factors; radiometric quality of the multitemporal imagery, relatively low observation frequency, the uncertainty of reference data and the regression tree model employed. Furthermore, the medium spatial resolution of Landsat images restricts the accurate mapping of the heights of the tallest forests (Potapov et al., 2021). Lang et al. (2023) emphasizes that the HRCH model shows limitations stemming from the lower effective spatial resolution at which individual vegetation features can be identified. As a consequence of the GEDI reference data used to train the model, each map pixel effectively indicates the largest canopy-top height within a GEDI footprint (≈25 m diameter) centred at the pixel. Two reasons further impact the effective resolution: the model never explicitly detect high-frequency variations of the canopy height between adjacent pixels, and misalignments caused by the geolocation uncertainty (15-20 m) of the GEDI v1 data (Lang et al., 2023).

On a global scale, Lang et al. (2023) conclude that some regions are subject to overall high predictive uncertainty, including tropical regions, but also regions in northern latitudes. This underlines the importance of modeling the predictive uncertainty of the canopy height map. Moudrý et al. (2024) report that predictive uncertainty correlates well, at least as far as errors up to 12 m, with the absolute canopy height error of the HRCH map.

Moudrý et al. (2024) find larger errors in GMTCH than those found by Tolan et al. (2024). Moudrý et al. (2024) report that GMTCH consistently underestimated all canopies heights with MEs from -7 m to -12 m and RMSEs ranging from 10 m to 17 m.

The findings from the accuracy assessment of the three global models (GFCH, HRCH, and GMTCH) show that GMTCH and GFCH consistently underestimate the height of all canopies regardless of their height (Moudrý et al., 2024). Additionally, Moudrý et al. (2024) conclude that HRCH outperforms GMTCH and GFCH in estimating the height of tall canopies (taller than 30 m). The spatial resolutions of GMTCH drive the need to emphasize that modeled global canopy height maps require high geolocation accuracy of input data for modeling procedures.

Global canopy height models represent a significant advancement to map forest attributes. When combined with unprecedented high spatial resolutions, these maps offer new opportunities to gain deeper insights into forests from a global perspective. However, the errors still exceed by a factor of 1.4 to 8.5 times the accepted accuracy for heights, considering the RMSEs of the global models surveyed in this study. It should be noted, that tree height estimates with an RMSE greater than 3 m led to significant errors in tropical forests when height is used to calculate biomass, especially for the largest trees (Ojoatre et al., 2019). As mentioned, terrain roughness, forest cover density, tree phenology, and environmental conditions significantly affect the accuracy of global maps.

Fassnacht et al. (2024) address challenges related to the uptake of remotely sensed data in forestry concerning four specific topics: a) National Forest inventories, in this framework, it also encompasses landscape analysis, b) Management-level forest inventory, c) Plot-level measurements, and d) Temporally continuous forest monitoring. Canopy height maps are relevant for all these topics.

Topic a): Based on the assessed accuracy of the global canopy heights maps, HRCH can potentially be applied to simple relationships for biodiversity research at the landscape level as Moudrý et al. (2024) demonstrated. Currently, HRCH serves as auxiliary information for land cover classification in a country level (MapBiomas, 2024). The performance of vertical accuracy for height estimations of ATL08 is utilized for forest aboveground biomass retrieval at a regional scale by combining strong nighttime beams with optical imagery, as well as meteorological and topographic datasets (Ma et al., 2025). Compared to GFCH and HRCH, the sensitivity (i.e., recognizing transitions between forests and grasslands) of GMTCH is greater, providing better estimate of horizontal heterogeneity in canopy height at small spatial scales (Moudrý et al., 2024).

The use of global canopy heights maps at management- and plot-level (topics b and c) may require more accurate height estimates than the current ones. The efforts to produce periodically global canopy height maps would provide a valuable tool for forest change detection (Topic d).

Since the availability of the recent global canopy height models, and to overcome limiting factors, the range of data integration has been broadened to continuously map forest height at higher temporal-spatial resolution. Statewide models for estimating canopy heights, particularly to enhance methodologies applied in mountain forests (Kacic et al., 2023; Schwartz et al., 2024; Alvites et al., 2025), along with countrywide approaches for detecting changes in canopy heights at the tree level (Fogel et al., 2024) have achieved notable progress in the field of canopy height mapping. These developments offer valuable insights for enhancing global models, expanding their applications topics.

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JDL designed the study and wrote the manuscript.

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