**Tracking Forest Height Growth Over Time with ICESat-2 ATL08**

William Poncy1, Valerie Thomas1, Randolph Wynne1, P. Corey Green1, Phil Radtke1

1Department of Forest Resources and Environmental Conservation, Virginia Tech, Blacksburg, VA, USA

**Abstract**

Quantification of forest structure is necessary for forest inventory, growth prediction, and carbon stock estimates. Since 2018, the ICESat-2 mission has estimated ground and canopy heights in 100-meter data segments across the globe. In this research, we use five years of ICESat-2 ATL08 data to identify canopy height growth in a coastal region of North Carolina, a site selected for its high industrial forest activity. ATL08 canopy height estimations demonstrate strong (R2 = 0.88, RMSE = 2.64 meters) alignment with coincident airborne laser scanning. Because ICESat-2 covers different locations each cycle, equivalence tests were used to show that ICESat-2 coverage locations are equivalent within a margin of 2 meters of canopy height. U.S. Forest Service plots within our study area provide a reference canopy height growth rate of 0.34 meters per year, and a net growth of 1.68 meters over a five-year period. Multiple statistical approaches reveal that canopy height growth is detectable within five years of ATL08 data. However, stratifying growth trends by forest cover type and disturbance history yields nuanced results, as these factors are likely to influence each other. Ultimately, this research aims to serve as a proof-of-concept for using multiple years of spaceborne LiDAR data to identify canopy height growth. Future research should use spaceborne LiDAR to identify growth in other regions of the globe, as solid results could solidify the use of the ATL08 product in global forest growth monitoring.

**Keywords**

remote sensing, forests, LiDAR, ICESat-2

**Highlights**

* ICESat-2 ATL08 data are used to identify canopy height growth
* ATL08-derived growth rates align well with reference data
* Forest cover type & disturbance history have complex influence on growth rates
* Recommendations for tracking forest growth with ATL08 data are provided

**Graphical Abstract**

1. **Introduction**

Supporting forest ecosystems is critical to combating climate change as they are the backbone of the land carbon sink, covering ~31% of terrestrial land area and sequestering twice as much carbon as they emit (FAO and UNEP, 2020; Harris and Gibbs, 2021; Psistaki et al., 2024). However, climatic changes can change tree regeneration capacity and result in stress-induced mortality, altering the species composition of forests (Khaine and Woo, 2015). Additionally, forest disturbance regimes are sensitive to climatic changes, with warming temperatures likely to increase the frequency of fire, insect, and pathogen-based disturbances in coming years (Seidl et al., 2017). To effectively assess forest resilience in the face of evolving disturbance regimes, dynamic ecosystem models require information on forest structural diversity over large scales (Mitchell et al., 2023).

Light detection and ranging (LiDAR) has seen growing use in forest remote sensing. LiDAR can penetrate the canopy layer to describe the subcanopy vegetation and topography of a forest ecosystem, which have strong influence on drought response and wildfire susceptibility (Jarron et al., 2020; Zhao et al., 2022). LiDAR is also used for estimating aboveground biomass of forest ecosystems—an essential task for quantifying the global carbon budget and upholding international climate emissions agreements—more accurately than optical sensors (Neuenschwander et al., 2023; Zolkos et al., 2013). Commonly, LiDAR data is used to describe the structural complexity of forests to infer ecosystem functions by quantifying traits like canopy cover, foliage height diversity, top rugosity, leaf area index, and leaf area density. This study uses canopy height as the primary forest structural characteristic, as tree height data is fundamental to forest management for estimating stem volume, describing stand health, and modeling forest biomass (Chen et al., 2023; Mielcarek et al., 2020).

Airborne laser scanning (ALS) distributes emitted light along an aircraft’s flight path (Maltamo et al., 2014), often used for research at scales larger than individual forest stands. ALS sensor technology can collect data at hundreds or thousands of points per square meter, overcoming the difficulties of traditional sampling techniques in remote or topographically complex areas (Sumnall et al., 2022; Wilkes et al., 2015; Xiang et al., 2024). The spatial coverage of ALS is invaluable for forest research across ecological gradients, with programs like the U.S. Geological Survey (USGS) 3D Elevation Program and the National Ecological Observatory Network Airborne Observation Platform providing ALS data for a range of forested environments. While the accuracy of tree height estimations from ALS are dependent upon species composition, aircraft flight height, and scanner pulse density, LiDAR sensors often underestimate tree height due to the unlikely nature of laser pulses returning from the top of a tree (Yu et al., 2004; Zhao et al., 2018). Multiple studies have found that tree height can be estimated by ALS to within half a meter for pine species (Andersen et al., 2006; Roberts et al., 2005). ALS data from the 3D Elevation Program (3DEP), used in this study, has been used to create high-resolution canopy height models and accurately predict the dominant height and site index of forests (Oh et al., 2022; Ribas-Costa et al., 2024).

Forest height growth is itself heavily influenced by external factors, and estimating year-over-year height growth with ALS could be subject to non-trivial errors due to ALS point density, the method of tree identification in point cloud data, and time interval between measurements (Guerra-Hernández et al., 2021; Socha et al., 2020). Identifying forest height growth with repeat ALS requires ample time between collections for the growth to exceed the noise of single point-in-time measurements. In a study of spruce, pine, and birch, Hyyppä et al. (2003) found stand-level growth errors primarily below 5 centimeters in a 21-month timeframe. Using the same data, Yu et al. (2004) observed that plot-level growth could be determined within 10-15 centimeters. In a study of temperate, mature red pine, Hopkinson et al. (2008) observed an approximate growth rate of 0.3 meters per year, and that the LiDAR-estimated growth falls below an acceptable uncertainty value of 10% after 3 years. Despite impressive performance in estimating forest height and growth ALS data is not without its shortcomings, with collection costs prohibitive to highly repeat or global coverage (Hancock et al., 2021; Liu et al., 2019). Moreover, differences in ALS acquisition parameters even within the same program, namely point density, can yield variability in forest structural estimation (LaRue et al., 2022).

Estimates of aboveground biomass and density are critical to understanding the impacts of land use change on the global carbon cycle (Dubayah et al., 2022). To overcome limitations present in ALS, spaceborne LiDAR missions have been launched facilitating region-to-global scale ecosystem insights (Coops et al., 2021). These missions exchange repeated measurements of small, specific areas for broad spatial coverage, sampling earth’s surface during continued orbit throughout time. When harmonized with other data sources, spaceborne LiDAR data enables the creation of gridded biomass products at regional and global scales (Dubayah et al., 2022; Neuenschwander et al., 2024).

NASA’s Ice, Cloud, and Land Elevation Satellite (ICESat) mission collected global waveform LiDAR data from 2003 to 2009 with a laser altimeter system to quantify changes in polar icesheet elevation (Markus et al., 2017). However, ICESat-derived data products also saw use in efforts measuring land topography, vegetation canopy heights, and atmospheric composition (Schutz et al., 2005). More recently, NASA launched the Global Ecosystem Dynamics Investigation (GEDI) mission in late 2018 to directly assess land surface carbon balance and biodiversity using waveform LiDAR (Dubayah et al., 2020). Building on the success of the first ICESat mission, NASA also launched the ICESat-2 mission in September 2018 to continue measurements of ice sheet elevation through improvements in beam design, along-track sampling rate, and footprint diameter (Markus et al., 2017).

The ICESat-2 satellite employs the Advanced Topographic Laser Altimeter System (ATLAS), a photon-counting LiDAR instrument, to sample earth’s surface (Carabajal and Boy, 2020). ATLAS operates at a 532 nm (green) laser wavelength, optimized for maximal photon detection with current technology. Prior to exiting ATLAS, the laser is split into six beams arranged into three beam pairs, with each beam pair containing a strong and weak beam with an energy transmission ratio of 4:1 (Neumann et al., 2019).

For greater coverage of Earth’s surface, beams within a pair are separated by 90 meters and beam pairs are separated by ~3 kilometers (Markus et al., 2017). ATLAS’s photon-counting technology allows reduced laser power requirement, and therefore a smaller payload aboard the ICESat-2 bus (Sun et al., 2020). With a spacecraft velocity of ~7 km/s and a laser frequency of 10 kHz, the ATLAS instrument achieves an along-track sampling interval of 70 centimeters (Klotz et al., 2020). This generates strong overlap between shots to determine terrain slope both along and across the orbital track. In contrast to GEDI mission which collects data only within latitudes +51.6, ICESat-2 provides near-global coverage between 88° N and S (Markus et al., 2017; Pronk et al., 2024). Moreover, ICESat-2’s orbital altitude of ~500 km and 91-day repeat cycle facilitate analyses of seasonal variation for its coverage areas (Wang et al., 2024)

The consistency of surface measurements by the ATLAS instrument is influenced by atmospheric conditions and land cover attributes. Over highly reflective surfaces like land ice, up to 10 signal photons may be returned per laser pulse. Over vegetated areas with lower surface reflectance, the energy and detection ratio of ATLAS may drop to ~2.5:1, with only 0 to 4 signal photons returned per laser pulse (Neuenschwander et al., 2024, 2023). Though primarily designed for ice sheet monitoring, products for ICESat-2 data have been developed for characterizing ocean elevation, inland water height, and terrestrial vegetation. This research employs the ICESat-2 ATL08 data product, which estimates ground and canopy heights in 20-meter and 100-meter segments.

Assessing the performance of ATL08 segments in estimating canopy heights requires comparison against reference data, commonly from airborne laser scanning. While studies generally report an underestimation of canopy height by ATL08 segments, the magnitude of error varies with forest conditions. In a well-managed, primarily coniferous region of southern Finland, Neuenschwander et al. (2020) reported a mean bias of 3.05 m between ATL08 and ALS canopy heights. Malambo & Popescu (2021) found a mean bias of -1.71 m between ATL08 and ALS canopy heights across six biomes of the US, with the strongest agreement in temperate conifer forests (percent bias: -9.3%, percent mean absolute error: 26.2%), the lowest agreement in tropical/subtropical regions with scattered trees (percent bias: -7.2%, percent mean absolute error: 81.8%), and variation between sites within the same biome. In a wider study across 40 sites in the US, A. Liu et al. (2021) reported a mean bias of -0.77 m, and a mean absolute error of 4.33 m. Canopy height estimation errors are generally minimized in a range of ~40 to ~80% canopy over: sparse vegetation has an inherently low probability of generating photon returns to accurately describe canopy height, while in dense canopy cover photons may inadequately sample the underlying terrain, introducing error into the resulting canopy height estimation (Liu et al., 2021; Neuenschwander et al., 2023, 2020). ATL08 data collected at nighttime with the strong beam of the sensor consistently yield the lowest height estimation errors due to reduced atmospheric interference and greater energy output, and use of weak beam data is generally discouraged for canopy height estimation (Chen et al., 2023; Guerra-Hernández et al., 2022; Liu et al., 2021; Neuenschwander et al., 2020; Rai et al., 2024; Yu et al., 2022).

Ultimately, the accuracy of ATL08 canopy height estimation is a function of many factors, including acquisition characteristics (e.g., beam strength, time of collection), terrain variability, forest density, geolocation accuracy, atmospheric noise, local disturbance history, and temporal coincidence to reference data (Fernandez-Diaz et al., 2022; Malambo and Popescu, 2021; Neuenschwander et al., 2023; Rai et al., 2024). These challenges notwithstanding, ICESat-2’s near-global coverage and high geolocation accuracy (<6.5 m) offer a unique advantage over GEDI to track vegetation dynamics throughout time (Luthcke et al., 2021; Neuenschwander and Magruder, 2019). Still, the question remains as to whether spaceborne LiDAR can reliably detect forest height growth when and where other data sources are not available (Li et al., 2022; Malambo and Popescu, 2021).

By leveraging ICESat-2’s strengths and effectively handling limitations present in its data quality, this study uses multiple years of spaceborne LiDAR to assess forest height growth. To that end, we pose the following research questions:

1. To what extent can ICESat-2 ATL08 detect forest height growth over time?
2. How is this ability influenced by forest cover type and disturbance history?
3. **Materials and Methods**
   1. **Study Area**

Hurricane Florence, a slow moving category one hurricane, made landfall in coastal North Carolina on September 14th, 2018 (Callaghan, 2020). Florence brought record-breaking levels of rain, surpassing 30 inches of rain in some regions of North Carolina, resulting in 53 fatalities and an estimated $16-44 billion in damages to public and private infrastructure (Griffin et al., 2020; Paul et al., 2019). In response, the USGS 3DEP, under the Additional Supplemental Appropriations for Disaster Relief Act of 2019 (H.R. 2157), collected high-resolution ALS data to quantify the extent of hurricane damage and support infrastructure recovery efforts (Hinck and Stachyra, 2019). The study area of this research is defined as the collective boundaries of the 3DEP Hurricane Florence ALS projects (Figure 1). The study area comprises ~5.1 million hectares in the Eastern region of North Carolina.

**Figure 1 map**

The study area was selected for several factors. Repeat coverage by ICESat-2 is unlikely at the stand or plantation scale, and the collection of data to validate ATL08 canopy height estimations can be financially cumbersome. However, the chosen study area is large enough to ensure repeat coverage by ICESat-2 even after data quality filters, and contains wall-to-wall coverage of high-resolution ALS data. While topography has noticeable effects on ATL08 canopy height estimation (Liu et al., 2021; Malambo and Popescu, 2021), the study area contains low terrain variability, with an elevation standard deviation of **\_\_\_\_\_ meters and an average slope of \_\_\_\_\_ degrees.** As of 2023, the National Land Cover Database characterizes the study area as predominantly Woody Wetlands **(%)**, Ccultivated Crops **(%)**, and Evergreen Forest **(%).** Finally, the study area falls within the historical natural range of *Pinus taeda* (loblolly pine). As such, the regular tree spacing, consistent tree heights, and fast tree growth observed in the region’s forest plantations should facilitate canopy height growth identification in ATL08 data (Baker and Langdon, 1990).

* 1. **Data Products**

This research utilizes ICESat-2 ATL08 data to track canopy height growth over time. Land cover data from the Annual National Land Cover Database was used to isolate forested regions within the study area. The disturbance history of these forested regions was derived from the U.S. Forest Service’s Landscape Change Monitoring System. ALS data from the USGS 3DEP was used to validate ATL08 canopy height estimations, and assess spatial biases in the locations of ICESat-2 coverage. Finally, data from the U.S. Forest Service’s Forest Inventory and Analysis program provided local, repeat plot surveys for determining expected canopy height growth patterns within our study area. Furter details on each of these datasets are provided below.

* + 1. **ALS**

Hurricane Florence ALS data is contained in 11 projects of the USGS 3DEP flown between December 7th, 2019, and February 28th, 2020. All projects utilized the Reigl VQ 1560i or 1560ii instruments to collect data, meeting the Quality Level 1 requirements of the 3DEP LiDAR Base Specification. This guarantees an aggregate nominal pulse density of >8 points per square meter, and an absolute vertical accuracy (RMSE) of <10 centimeters in nonvegetated areas (U.S. Geological Survey, 2025). With this strong vertical accuracy and high point density, we considered this 3DEP ALS data to be adequate in serving as a reference for ATL08 canopy height estimations. USGS 3DEP LiDAR Point Clouds were accessed on **\_\_\_\_\_\_\_** , 2025 from m https://registry.opendata.aws/usgs-lidar. A custom Python script was created in Python **\_\_\_** to stream the 3DEP data from the Entwine Point Tiles format during data processing (**Python citation; see code appendix**).

* + 1. **ICESat-2 ATL08**

Photon measurements from the ATLAS instrument are aggregated into multiple data products. The Global Geolocated Photons (ATL03) data product records geolocated heights above the WGS84 ellipsoid for all photons downlinked by ATLAS (Neumann et al., 2023). From the geolocated photon data, the L3A Land and Vegetation Height (ATL08) data product is derived through a Differential, Regressive, and Gaussian Adaptive Nearest Neighbor method. This process filters out background noise and estimates land and surface vegetation heights, labelling individual photons as noise, ground, canopy, or top of canopy (Malambo and Popescu, 2024; Neuenschwander et al., 2020; Neuenschwander and Pitts, 2019). The ATL08 product reports several canopy height parameters for segments, including the mean, median, minimum, and maximum of relative and absolute heights for canopy photons. ATL08’s primary canopy height metric, *h\_canopy*, uses a segment’s 98th percentile relative canopy height to represent the top of canopy height, as true maximum canopy height may include background noise (Neuenschwander and Pitts, 2019). For this study, all available ATL08 Version 6 granules collected within the study area extent between October 14th, 2018 and December 31st, 2024 were downloaded from NASA’s Earthdata Search (https://search.earthdata.nasa.gov/search) using the Cygwin command-line interface. This provided 740 granules for further analysis.

* + 1. **National Land Cover Database**

To advance research on land surface characteristics within human-environmental systems, the USGS released the Annual National Land Cover Database (NLCD) Collection 1.1 Science Products. This suite of six data products provides annual land cover classification and land change assessments for the Conterminous U.S. for 1985 to 2024. It is created through a framework that leverages geospatial deep learning, continuous change detection, and probability-based post processing against the historical Landsat data record. Within the collection, the Land Cover data product categorizes the earth’s land surface into 16 broad natural and artificial cover types for each mapping year using a modified Anderson Level II classification system (Anderson et al., 1976). While ATL08 segments include native land cover information in the *segment\_landcover* attribute, it is derived from the Copernicus Land cover data product at a 100-meter resolution (Buchhorn et al., 2020). The NLCD Land Cover dataset was chosen for this research due to its higher spatial resolution, and alignment with historical forest disturbance data from the U.S. Forest Service. NLCD data used in this research was accessed from the Muli-Resolution Land Characteristics Consortium data archive (https://www.mrlc.gov/data). Land Cover for the Conterminous U.S was downloaded for **\_\_\_\_**, provided in a single-band TIFF raster at a 30-meter spatial resolution.

* + 1. **Landscape Change Monitoring System**

The Landscape Change Monitoring System (LCMS) is a suite of remotely sensed data products developed by the U.S. Forest Service to monitor landscape dynamics across the United States. LCMS relies on input spectral imagery from Landsat and Sentinel-2. From these inputs, clouds and cloud shadows are masked, imagery is assembled into an annual time series and temporally segmented, and incorporated with USGS 3DEP terrain data in a random forest model to generate products for vegetation cover Change, Land Cover, and Land Use (Housman et al., 2024).

The vegetation cover Change product is comprised of subproducts that categorize change processes into Fast Loss, Slow Loss, and Gain. Fast loss events indicate an abrupt disturbance to vegetation cover (fire, harvesting, etc), slow loss events indicate gradual structural or spectral decline, and gain indicates vegetation growth or recovery. A summary product is created for each of these processes with pixel values identifying the most recent occurrence of the given change between 1985 and 2023. For this research, the Fast Loss Change summary product for the Conterminous U.S. was downloaded from the LCMS Data Explorer (https://apps.fs.usda.gov/lcms-viewer/).

* + 1. **Forest Inventory & Analysis Program**

The Forest Inventory & Analysis Program is an effort by the U.S. Forest Service Research and Development Branch to monitor the distribution and health of forest resources in all 50 states, U.S. territories, and Freely Associated States ( Republic of Marshall Islands, Federated States of Micronesia, Republic of Palau; Renwick, 2023). A core tenet of the FIA is the Nationwide Forest Inventory (NFI), a network of forest plots that receive repeat measurements every 5-10 years. Depending on the plot, the NFI provides data on land use, soil characteristics, down woody material, understory vegetation, and individual tree height measurements. Though precise FIA plot locations are obscured for privacy concerns, the county of each plot record is specific with Census Bureau FIPS codes—a level of spatial accuracy sufficient for this research (Burrill et al., 2024)

* 1. **Data Processing**
     1. **ICESat-2 ATL08**

Careful handling of all potential sources of error in ATL08 data is necessary to optimize its application for given analyses (Feng et al., 2023; Li et al., 2022, 2020; Rai et al., 2024; Wang et al., 2024; Xi et al., 2022). First, raw ATL08 granules were processed in a custom Python script to extract metrics related to the vegetation conditions, terrain characteristics, and satellite operation for each 100-meter segment (see appendix for code). Segments were geolocated with the GeoPandas library from the *latitude* and *longitude* attributes (**Geopandas citation**), identifying the center coordinates of signal photons for each segment (Neuenschwander et al., 2023). The segments were then clipped to retain only those collected within the study area.

ATL08 segments were then processed in a custom Python script to apply data quality filters and intersect with land cover characteristics (see appendix for code). ATL08 segments with invalid (3.402e+38) canopy height values were removed. To minimize biases introduced by low-lying vegetation or high noise, canopy heights were filtered to values between 2 meters and a global maximum (Cao et al., 2016; Li et al., 2020; Rai et al., 2024). Following the approach of Malambo & Popescu (2024), the global maximum for canopy heights was calculated with *k \* P,* where *k* is a constant factor of 1.2, and *P* is the 98th percentile of all ATL08 canopy heights in the dataset. For our study area the calculated global maximum was (**global maximum)** meters. This was effective in removing erroneously high canopy heights estimated by the ATL08 algorithm. Further filters selected only segments collected by strong beams at nighttime within the months of May to September to minimize the effect of solar noise and vegetation phenology on canopy height estimation (Neuenschwander et al., 2020). As done by Malambo & Popescu (2024), segments with a multiple scattering warning flag greater than zero or a cloud confidence flag greater than one were removed to mitigate atmospheric interference.

Segment points were intersected with annual NLCD land cover to determine the land cover of each segment’s centroid for the year of 2023. Forested segments were identified by selecting only those with NLCD values of 41 (Deciduous Forest), 42 (Evergreen Forest), 43 (Mixed Forest), or 90 (Woody Wetlands). The segments were intersected with the annual LCMS Fast Loss change product to provide insight into the disturbance history of these forests. For segments with a disturbance event identified by the Fast Loss product, the years since the last disturbance was calculated as the difference between the year of ICESat-2 collection and the most recent disturbance year. For this research, segments with disturbances occurring after the year of ICESat-2 collection were removed, as ATL08 canopy heights may no longer reflect the forest conditions present. Additionally, segments with 3 years or less since the last disturbance event were removed to provide a buffer of forest regrowth and recovery from disturbance.

**Figure 2 map of ATL08 tracks**

* + 1. **Extracting ALS Data Within ATL08 Segments**

For this research it is necessary to extract 2020 ALS data within each individual ATL08 segment. To generate the rectangular polygons of the ATL08 segments, a polygon of 100 x 11 meters was created around the centroid coordinates of each segment, and rotated to align with the ICESat-2 track inclination (see appendix for code; Neuenschwander et al., 2020; Rai et al., 2024). The polygons were reprojected to the Web Mercator projection system (EPSG:3857), which the 3DEP ALS data uses in its native storage format (Hobu, Inc., 2025). These polygons serve as cropping geometries for the ALS data.

ALS data was processed in a custom PDAL pipeline (Figure 3; PDAL Contributors, 2025; see appendix for code). For each ATL08 segment, ALS data was streamed from any 3DEP project intersecting the polygon’s extent. The *filters.smrf* function was used to interpolate the ground surface while minimizing Type I errors (Pingel et al., 2013), which could have yielded inaccurate canopy height estimation. Heights above the interpolated ground surface were calculated with a nearest neighbor approach using the *filters.hag\_nn* function (Ribas-Costa et al., 2024). The normalized point cloud was cropped to the geometry of the respective polygon to match the polygon’s along-track inclination (Figure 4).

**Figure 3 of ALS workflow**

**Figure 4 of ALS crop**

For each ATL08 segment, the normalized ALS point cloud was converted to a Pandas DataFrame to facilitate analyses (The pandas development team, 2025). To match the filters applied to ATL08 data, we selected only non-ground returns with heights above ground between 2 and the previously determined global maximum of **(global maximum)** meters. These were deemed as *vegetation* returns, from which the following metrics were calculated for the return heights: mean, median, minimum, maximum, and the 90th, 95th, 98th, and 99th percentiles. The ratio of vegetation returns to total returns provided an approximation of vegetation density (Neuenschwander et al., 2020). This DataFrame of ALS metrics was joined to the corresponding ATL08 segment using a unique identifier. However, due to the overlapping collection scheme of 3DEP projects some ATL08 segments intersected with multiple ALS datasets, resulting in duplicate segments with vegetation metrics calculated for more than one ALS project (Figure)

**Figure 5 of ALS overlap**

In the instance of duplicate segments, only the segment associated with the ALS project providing the highest number of vegetation returns was retained.

Moreover, the 3DEP project boundaries are generalized. Cropping ATL08 segments to the 3DEP Hurricane Florence projects (the study area) yielded some ATL08 segments with no ALS returns within their bounds. These were also removed from analyses, resulting in a final **(working set*)*** of ATL08 segments. In summary, the working set contains 6 years (2019 - 2024) of ICESat-2 ATL08 segments for which vegetation height metrics were also calculated from 2020 airborne laser scanning within each segment’s geometry.

* + 1. **Retrieving Study Area FIA Data**
  1. **Data Analysis**
     1. **Statistical Approaches Used**
        1. **Linear Regression Model**
        2. **Equivalence Test**
        3. **Wilcoxon Rank-Sum Test**
        4. **Mann-Kendall Test**
        5. **Bonferroni Correction**
     2. **Validating ATL08 Canopy Heights with ALS**
     3. **Addressing Sampling Bias of ICESat-2 Data Collection**
        1. **Sample Representation**
        2. **Sample Equivalence**
     4. **FIA-Derived Tree Height Growth**
     5. **Assessing Canopy Height Growth with ATL08**

1. **Results**
   1. **Accuracy of ATL08 Canopy Height Estimation**
   2. **Study Area Homogeneity**
   3. **Reference Growth**
   4. **ATL08-Derived Growth**
2. **Discussion**
3. **Conclusion**

**Acknowledgements**

**CRediT authorship contribution statement**

**Funding sources**

**Appendices**

**References**

Andersen, H.-E., Reutebuch, S.E., McGaughey, R.J., 2006. A Rigorous Assessment of Tree Height Measurements Obtained Using Airborne Lidar and Conventional Field Methods. Can. J. Remote Sens. 32, 355–366. https://doi.org/10.5589/m06-030

Anderson, J.R., Hardy, E.E., Roach, J.T., Witmer, R.E., 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data, Professional Paper. US Geological Survey. https://doi.org/10.3133/pp964

Baker, J.B., Langdon, G.O., 1990. Pinus Taeda L. Loblolly Pine, in: Silvics of North America. U.S. Deptartment of Agriculture, Forest Service, Washington, D.C., pp. 505–512.

Buchhorn, M., Smets, B., Bertels, L., Roo, B.D., Lesiv, M., Tsendbazar, N.-E., Herold, M., Fritz, S., 2020. Copernicus Global Land Service: Land Cover 100m: Collection 3: Epoch 2019: Globe. https://doi.org/10.5281/ZENODO.3939050

Burrill, E.A., DiTommaso, A.M., Turner, J.A., Pugh, S.A., Christensen, G., Kralicek, K.M., Perry, C.J., Lepine, L.C., Walker, D.M., Conkling, B.L., 2024. The Forest Inventory and Analysis Database, FIADB User Guides. U.S. Department of Agriculture, Forest Service.

Callaghan, J., 2020. Extreme Rainfall and Flooding from Hurricane Florence. Trop. Cyclone Res. Rev. 9, 172–177. https://doi.org/10.1016/j.tcrr.2020.07.002

Cao, L., Coops, N.C., Innes, J.L., Sheppard, S.R.J., Fu, L., Ruan, H., She, G., 2016. Estimation of Forest Biomass Dynamics in Subtropical Forests Using Multi-Temporal Airborne LiDAR Data. Remote Sens. Environ. 178, 158–171. https://doi.org/10.1016/j.rse.2016.03.012

Carabajal, C.C., Boy, J.-P., 2020. ICESat-2 Altimetry as Geodetic Control. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLIII-B3-2020, 1299–1306. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-1299-2020

Chen, F., Zhang, X., Wang, Longyu, Du, B., Dang, S., Wang, Linwei, 2023. Systematic Evaluation of Multi-Resolution ICESat-2 Canopy Height Data: A Case Study of the Taranaki Region. Remote Sens. 15, 5686. https://doi.org/10.3390/rs15245686

Coops, N.C., Tompalski, P., Goodbody, T.R.H., Queinnec, M., Luther, J.E., Bolton, D.K., White, J.C., Wulder, M.A., Van Lier, O.R., Hermosilla, T., 2021. Modelling LiDAR-Derived Estimates of Forest Attributes Over Space and Time: A Review of Approaches and Future Trends. Remote Sens. Environ. 260, 112477. https://doi.org/10.1016/j.rse.2021.112477

Dubayah, R., Armston, J., Healey, S.P., Bruening, J.M., Patterson, P.L., Kellner, J.R., Duncanson, L., Saarela, S., Ståhl, G., Yang, Z., Tang, H., Blair, J.B., Fatoyinbo, L., Goetz, S., Hancock, S., Hansen, M., Hofton, M., Hurtt, G., Luthcke, S., 2022. GEDI Launches a New Era of Biomass Inference from Space. Environ. Res. Lett. 17, 095001. https://doi.org/10.1088/1748-9326/ac8694

Dubayah, R., Blair, J.B., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., Hofton, M., Hurtt, G., Kellner, J., Luthcke, S., Armston, J., Tang, H., Duncanson, L., Hancock, S., Jantz, P., Marselis, S., Patterson, P.L., Qi, W., Silva, C., 2020. The Global Ecosystem Dynamics Investigation: High-Resolution Laser Ranging of the Earth’s Forests and Topography. Sci. Remote Sens. 1, 100002. https://doi.org/10.1016/j.srs.2020.100002

FAO and UNEP, 2020. The State of the World’s Forests 2020, Forests, biodiversity, and people. FAO and UNEP, Rome. https://doi.org/10.4060/ca8642en

Feng, T., Duncanson, L., Montesano, P., Hancock, S., Minor, D., Guenther, E., Neuenschwander, A., 2023. A Systematic Evaluation of Multi-Resolution Icesat-2 Atl08 Terrain and Canopy Heights in Boreal Forests. Remote Sens. Environ. 291, 113570. https://doi.org/10.1016/j.rse.2023.113570

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 J. Sel. Top. Appl. Earth Obs. Remote Sens. 15, 2956–2970. https://doi.org/10.1109/JSTARS.2022.3163208

Griffin, M., Malsick, M., Mizzell, H., Moore, L., 2020. Historic Rainfall and Record-Breaking Flooding from Hurricane Florence in the Pee Dee Watershed. J. S. C. Water Resour. 28–35. https://doi.org/10.34068/JSCWR.06.03

Guerra-Hernández, J., Arellano-Pérez, S., González-Ferreiro, E., Pascual, A., Sandoval Altelarrea, V., Ruiz-González, A.D., Álvarez-González, J.G., 2021. Developing a Site Index Model for P. Pinaster Stands in NW Spain by Combining Bi-Temporal ALS Data and Environmental Data. For. Ecol. Manag. 481, 118690. https://doi.org/10.1016/j.foreco.2020.118690

Guerra-Hernández, J., Narine, L.L., Pascual, A., Gonzalez-Ferreiro, E., Botequim, B., Malambo, L., Neuenschwander, A., Popescu, S.C., Godinho, S., 2022. Aboveground Biomass Mapping by Integrating ICESat-2, Sentinel-1, Sentinel-2, ALOS2/PALSAR2, and Topographic Information in Mediterranean Forests. GIScience Remote Sens. 59, 1509–1533. https://doi.org/10.1080/15481603.2022.2115599

Hancock, S., McGrath, C., Lowe, C., Davenport, I., Woodhouse, I., 2021. Requirements for a Global Lidar System: Spaceborne Lidar with Wall-to-Wall Coverage. R. Soc. Open Sci. 8, 211166. https://doi.org/10.1098/rsos.211166

Harris, N., Gibbs, D., 2021. Forests Absorb Twice As Much Carbon As They Emit Each Year.

Hinck, J.E., Stachyra, J., 2019. 2019 Disaster Relief Act: USGS Recovery Activities (USGS Numbered Series No. 2019–3066), Fact Sheet. Columbia Environmental Research Center, U.S. Geological Survey, Reston, VA.

Hobu, Inc., 2025. USGS 3DEP LiDAR Point Clouds.

Housman, I.W., Heyer, J.P., Hardwick, E.A., Leatherman, L., Beck, H., Lecker, J., Megown, K., Ross, J., 2024. Forest Service Landscape Change Monitoring System Methods (GTAC-10252- RPT4 No. Version 2023.9). U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, Salt Lake City, UT.

Jarron, L.R., Coops, N.C., MacKenzie, W.H., Tompalski, P., Dykstra, P., 2020. Detection of Sub-Canopy Forest Structure Using Airborne LiDAR. Remote Sens. Environ. 244, 111770. https://doi.org/10.1016/j.rse.2020.111770

Khaine, I., Woo, S.Y., 2015. An Overview of Interrelationship Between Climate Change and Forests. For. Sci. Technol. 11, 11–18. https://doi.org/10.1080/21580103.2014.932718

Klotz, B.W., Neuenschwander, A., Magruder, L.A., 2020. High‐Resolution Ocean Wave and Wind Characteristics Determined by the ICESat‐2 Land Surface Algorithm. Geophys. Res. Lett. 47. https://doi.org/10.1029/2019gl085907

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, e4209. https://doi.org/10.1002/ecs2.4209

Li, B., Zhao, T., Su, X., Fan, G., Zhang, W., Deng, Z., Yu, Y., 2022. Correction of Terrain Effects on Forest Canopy Height Estimation Using ICESat-2 and High Spatial Resolution Images. Remote Sens. 14, 4453. https://doi.org/10.3390/rs14184453

Li, W., Niu, Z., Shang, R., Qin, Y., Wang, L., Chen, H., 2020. High-Resolution Mapping of Forest Canopy Height Using Machine Learning by Coupling ICESat-2 LiDAR with Sentinel-1, Sentinel-2 and Landsat-8 Data. Int. J. Appl. Earth Obs. Geoinformation 92, 102163. https://doi.org/10.1016/j.jag.2020.102163

Liu, A., Cheng, X., Chen, Z., 2021. Performance Evaluation of GEDI and ICESat-2 Laser Altimeter Data for Terrain and Canopy Height Retrievals. Remote Sens. Environ. 264, 112571. https://doi.org/10.1016/j.rse.2021.112571

Liu, M., Popescu, S., Malambo, L., 2019. Feasibility of Burned Area Mapping Based on ICESAT−2 Photon Counting Data. Remote Sens. 12, 24. https://doi.org/10.3390/rs12010024

Luthcke, S.B., Thomas, T.C., Pennington, T.A., Rebold, T.W., Nicholas, J.B., Rowlands, D.D., Gardner, A.S., Bae, S., 2021. ICESat‐2 Pointing Calibration and Geolocation Performance. Earth Space Sci. 8, e2020EA001494. https://doi.org/10.1029/2020EA001494

Malambo, L., Popescu, S., 2024. Mapping Vegetation Canopy Height Across the Contiguous United States Using ICESat-2 and Ancillary Datasets. Remote Sens. Environ. 309, 114226. https://doi.org/10.1016/j.rse.2024.114226

Malambo, L., Popescu, S.C., 2021. Assessing the Agreement of ICESat-2 Terrain and Canopy Height with Airborne Lidar Over US Ecozones. Remote Sens. Environ. 266, 112711. https://doi.org/10.1016/j.rse.2021.112711

Maltamo, M., Næsset, E., Vauhkonen, J. (Eds.), 2014. Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies, Managing Forest Ecosystems. Springer Netherlands, Dordrecht. https://doi.org/10.1007/978-94-017-8663-8

Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., Farrell, S., Fricker, H., Gardner, A., Harding, D., Jasinski, M., Kwok, R., Magruder, L., Lubin, D., Luthcke, S., Morison, J., Nelson, R., Neuenschwander, A., Palm, S., Popescu, S., Shum, C., Schutz, B.E., Smith, B., Yang, Y., Zwally, J., 2017. The Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2): Science Requirements, Concept, and Implementation. Remote Sens. Environ. 190, 260–273. https://doi.org/10.1016/j.rse.2016.12.029

Mielcarek, M., Kamińska, A., Stereńczak, K., 2020. Digital Aerial Photogrammetry (DAP) and Airborne Laser Scanning (ALS) as Sources of Information About Tree Height: Comparisons of the Accuracy of Remote Sensing Methods for Tree Height Estimation. Remote Sens. 12, 1808. https://doi.org/10.3390/rs12111808

Mitchell, J.C., Kashian, D.M., Chen, X., Cousins, S., Flaspohler, D., Gruner, D.S., Johnson, J.S., Surasinghe, T.D., Zambrano, J., Buma, B., 2023. Forest Ecosystem Properties Emerge from Interactions of Structure and Disturbance. Front. Ecol. Environ. 21, 14–23. https://doi.org/10.1002/fee.2589

Neuenschwander, A., Duncanson, L., Montesano, P., Minor, D., Guenther, E., Hancock, S., Wulder, M.A., White, J.C., Purslow, M., Thomas, N., Mandel, A., Feng, T., Armston, J., Kellner, J.R., Andersen, H.E., Boschetti, L., Fekety, P., Hudak, A., Pisek, J., Sánchez-López, N., Stereńczak, K., 2024. Towards Global Spaceborne LiDAR Biomass: Developing and Applying Boreal Forest Biomass Models for ICESat-2 Laser Altimetry Data. Sci. Remote Sens. 10, 100150. https://doi.org/10.1016/j.srs.2024.100150

Neuenschwander, A., Guenther, E., White, J.C., Duncanson, L., Montesano, P., 2020. Validation of ICESat-2 Terrain and Canopy Heights in Boreal Forests. Remote Sens. Environ. 251, 112110. https://doi.org/10.1016/j.rse.2020.112110

Neuenschwander, A., Magruder, L.A., 2019. Canopy and Terrain Height Retrievals with ICESat-2: A First Look. Remote Sens. 11, 1721. https://doi.org/10.3390/rs11141721

Neuenschwander, A., Pitts, K., 2019. The ATL08 Land and Vegetation Product for the ICESat-2 Mission. Remote Sens. Environ. 221, 247–259. https://doi.org/10.1016/j.rse.2018.11.005

Neuenschwander, A., Pitts, K., Jelley, B.J., Robbins, J., Markel, J., Popescu, S., Nelson, R., Harding, D., Pederson, Klotz, B., Sheridan, R., 2023. Ice, Cloud, and Land Elevation Satellite (ICESat-2) Project Algorithm Theoretical Basis Document (ATBD) for Land - Vegetation Along-Track Products (ATL08), version 6. https://doi.org/10.5067/8ANPSL1NN7YS

Neumann, T.A., Brenner, A., Hancock, D., Robins, J., Saba, J., Harbeck, K., Gibbons, A., Lee, J., Luthcke, S., Rebold, T., 2023. Ice, Cloud, and Land Elevation Satellite (ICESat-2) Project Algorithm Theoretical Basis Document (ATBD) for Global Geolocated Photons ATL03, version 6. https://doi.org/10.5067/GA5KCLJT7LOT

Neumann, T.A., Martino, A.J., Markus, T., Bae, S., Bock, M.R., Brenner, A.C., Brunt, K.M., Cavanaugh, J., Fernandes, S.T., Hancock, D.W., Harbeck, K., Lee, J., Kurtz, N.T., Luers, P.J., Luthcke, S.B., Magruder, L., Pennington, T.A., Ramos-Izquierdo, L., Rebold, T., Skoog, J., Thomas, T.C., 2019. The Ice, Cloud, and Land Elevation Satellite – 2 Mission: A Global Geolocated Photon Product Derived from the Advanced Topographic Laser Altimeter System. Remote Sens. Environ. 233, 111325. https://doi.org/10.1016/j.rse.2019.111325

Oh, S., Jung, J., Shao, Guofan, Shao, Gang, Gallion, J., Fei, S., 2022. High-Resolution Canopy Height Model Generation and Validation Using USGS 3DEP LiDAR Data in Indiana, USA. Remote Sens. 14, 935. https://doi.org/10.3390/rs14040935

Paul, S., Ghebreyesus, D., Sharif, H.O., 2019. Brief Communication: Analysis of the Fatalities and Socio-Economic Impacts Caused by Hurricane Florence. Geosciences 9, 58. https://doi.org/10.3390/geosciences9020058

PDAL Contributors, 2025. PDAL Point Data Abstraction Library.

Pingel, T.J., Clarke, K.C., McBride, W.A., 2013. An Improved Simple Morphological Filter for the Terrain Classification of Airborne LiDAR Data. ISPRS J. Photogramm. Remote Sens. 77, 21–30. https://doi.org/10.1016/j.isprsjprs.2012.12.002

Pronk, M., Eleveld, M., Ledoux, H., 2024. Assessing Vertical Accuracy and Spatial Coverage of ICESat-2 and GEDI Spaceborne Lidar for Creating Global Terrain Models. Remote Sens. 16, 2259. https://doi.org/10.3390/rs16132259

Psistaki, K., Tsantopoulos, G., Paschalidou, A., 2024. An Overview of the Role of Forests in Climate Change Mitigation. Sustainability 16. https://doi.org/10.3390/su16146089

Rai, N., Ma, Q., Poudel, K.P., Himes, A., Meng, Q., 2024. Evaluating the Uncertainties in Forest Canopy Height Measurements Using ICESat-2 Data. J. Remote Sens. 4, 0160. https://doi.org/10.34133/remotesensing.0160

Renwick, K., 2023. 2022 Forest Inventory and Analysis Business Report (Business Report). U.S. Department of Agriculture, Forest Service, Research and Development, Forest Inventory and Analysis Program, Washington, D.C.

Ribas-Costa, V.A., Gastón, A., Cook, R.L., 2024. Modeling Dominant Height with USGS 3DEP LiDAR to Determine Site Index in Even-Aged Loblolly Pine (Pinus Taeda L.) Plantations in the Southeastern Us. For. Int. J. For. Res. cpae034. https://doi.org/10.1093/forestry/cpae034

Roberts, S.D., Dean, T.J., Evans, D.L., McCombs, J.W., Harrington, R.L., Glass, P.A., 2005. Estimating Individual Tree Leaf Area in Loblolly Pine Plantations Using LiDAR-Derived Measurements of Height and Crown Dimensions. For. Ecol. Manag. 213, 54–70. https://doi.org/10.1016/j.foreco.2005.03.025

Schutz, B.E., Zwally, H.J., Shuman, C.A., Hancock, D., DiMarzio, J.P., 2005. Overview of the ICESat Mission. Geophys. Res. Lett. 32, 2005GL024009. https://doi.org/10.1029/2005GL024009

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M.J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T.A., Reyer, C.P.O., 2017. Forest Disturbances Under Climate Change. Nat. Clim. Change 7, 395–402. https://doi.org/10.1038/nclimate3303

Socha, J., Hawryło, P., Stereńczak, K., Miścicki, S., Tymińska-Czabańska, L., Młocek, W., Gruba, P., 2020. Assessing the Sensitivity of Site Index Models Developed Using Bi-Temporal Airborne Laser Scanning Data to Different Top Height Estimates and Grid Cell Sizes. Int. J. Appl. Earth Obs. Geoinformation 91, 102129. https://doi.org/10.1016/j.jag.2020.102129

Sumnall, M.J., Albaugh, T.J., Carter, D.R., Cook, R.L., Hession, W.C., Campoe, O.C., Rubilar, R.A., Wynne, R.H., Thomas, V.A., 2022. Effect of Varied Unmanned Aerial Vehicle Laser Scanning Pulse Density on Accurately Quantifying Forest Structure. Int. J. Remote Sens. 43, 721–750. https://doi.org/10.1080/01431161.2021.2023229

Sun, T., Qi, J., Huang, H., 2020. Discovering Forest Height Changes Based on Spaceborne Lidar Data of ICESat-1 in 2005 and ICESat-2 in 2019: A Case Study in the Beijing-Tianjin-Hebei Region of China. For. Ecosyst. 7, 53. https://doi.org/10.1186/s40663-020-00265-w

The pandas development team, 2025. pandas-dev/pandas: Pandas. https://doi.org/10.5281/ZENODO.15831829

U.S. Geological Survey, 2025. 3DEP LiDAR Base Specification.

Wang, X., Liang, X., Gong, W., Häkli, P., Wang, Y., 2024. Accuracy Fluctuations of ICESat-2 Height Measurements in Time Series. Int. J. Appl. Earth Obs. Geoinformation 135, 104234. https://doi.org/10.1016/j.jag.2024.104234

Wilkes, P., Jones, S.D., Suarez, L., Haywood, A., Woodgate, W., Soto-Berelov, M., Mellor, A., Skidmore, A.K., 2015. Understanding the Effects of ALS Pulse Density for Metric Retrieval Across Diverse Forest Types. Photogramm. Eng. Remote Sens. 81, 625–635. https://doi.org/10.14358/PERS.81.8.625

Xi, Z., Xu, H., Xing, Y., Gong, W., Chen, G., Yang, S., 2022. Forest Canopy Height Mapping by Synergizing ICESat-2, Sentinel-1, Sentinel-2 and Topographic Information Based on Machine Learning Methods. Remote Sens. 14, 364. https://doi.org/10.3390/rs14020364

Xiang, B., Wielgosz, M., Kontogianni, T., Peters, T., Puliti, S., Astrup, R., Schindler, K., 2024. Automated Forest Inventory: Analysis of High-Density Airborne LiDAR Point Clouds with 3D Deep Learning. Remote Sens. Environ. 305, 114078. https://doi.org/10.1016/j.rse.2024.114078

Yu, J., Nie, S., Liu, W., Zhu, X., Lu, D., Wu, W., Sun, Y., 2022. Accuracy Assessment of ICESat-2 Ground Elevation and Canopy Height Estimates in Mangroves. IEEE Geosci. Remote Sens. Lett. 19, 1–5. https://doi.org/10.1109/LGRS.2021.3107440

Yu, X., Hyyppä, J., Kaartinen, H., Maltamo, M., 2004. Automatic Detection of Harvested Trees and Determination of Forest Growth Using Airborne Laser Scanning. Remote Sens. Environ. 90, 451–462. https://doi.org/10.1016/j.rse.2004.02.001

Zhao, H., Wu, J., Wang, A., Guan, D., Liu, Y., 2022. Microtopography Mediates the Climate–Growth Relationship and Growth Resilience to Drought of Pinus Tabulaeformis Plantation in the Hilly Site. Front. Plant Sci. 13, 1060011. https://doi.org/10.3389/fpls.2022.1060011

Zhao, K., Suarez, J.C., Garcia, M., Hu, T., Wang, C., Londo, A., 2018. Utility of Multitemporal LiDAR for Forest and Carbon Monitoring: Tree Growth, Biomass Dynamics, and Carbon Flux. Remote Sens. Environ. 204, 883–897. https://doi.org/10.1016/j.rse.2017.09.007

Zolkos, S.G., Goetz, S.J., Dubayah, R., 2013. A Meta-Analysis of Terrestrial Aboveground Biomass Estimation Using Lidar Remote Sensing. Remote Sens. Environ. 128, 289–298. https://doi.org/10.1016/j.rse.2012.10.017