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

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**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**
     2. **Extracting ALS Data Within ATL08 Segments**
     3. **Retrieving Study Area FIA Data**
  2. **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**

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**Appendices**

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