

Using ICESat-2 ATL08 heights and Landsat time series to assess the age-height relationship of southern yellow pines in the US

Sonia Sharma Banjade^{a,*}, Randolph H. Wynne^a, Valerie A. Thomas^a, Patrick C. Green^a, Todd A. Schroeder^b

^a Department of Forest Resources and Environmental Conservation, Virginia Polytechnic Institute and State University, USA

^b USDA Forest Service, Southern Research Station, Forest Inventory and Analysis, Knoxville, TN, USA

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ABSTRACT

It is critical to understand the age-height relationship in actively managed pine plantations to evaluate forest productivity and inform sustainable forest management practices. This study utilized the spaceborne lidar data from ICESat-2 ATL08 and Landsat-derived disturbance maps to assess the site index for actively managed pine plantations across the southeastern United States. Specifically, we (1) assessed the agreement between ICESat-2 ATL08 canopy heights and airborne laser scanning (ALS) data, (2) showed the distribution of canopy height by age for the actively managed pine stands, and (3) compared the site index guide curve derived using ICESat-2 and Landsat data with the FIA-derived site index guide curve.

We analyzed over 137,998 ICESat-2 ATL08 segments intersecting pine plantation locations and LCMS Fast Loss. We identified plantation ages by subtracting the LCMS Fast Loss year from the ICESat-2 acquisition date. Actively managed stands were defined as those experiencing both thinning and harvesting. ICESat-2 ATL08 heights were compared to heights derived using airborne laser scanning (ALS) data from the USGS 3D Elevation Program. The heights were highly correlated in the assessed region ($R^2 = 0.90$), providing confidence in ICESat-2 ATL08 heights.

Despite the challenges with LCMS misclassifying thinning events as clear-cut disturbances, we developed a model using quantile regression relating the logarithm of ICESat-2 ATL08 height to the reciprocal of age, resulting in a regional site index guide curve. The ICESat-2-derived site index (19.9 m) closely matched the FIA-derived site index (19.8 m) at the base age of 25 years, as supported by the Cramér-von Mises test, indicating that the site index guide curves are statistically similar. The resulting site index map provides insights into spatial variability in regional forest productivity, emphasizing the utility of remote sensing data for large-scale forest monitoring and management

1. Introduction

Quantifying forest productivity is essential for effective forest management, as it provides valuable insights into various aspects of forestry, including silvicultural practices, carbon dioxide sequestration, biomass estimation, and understanding the impacts of climate change. The site index is a common measure of forest productivity related to the biophysical factors associated influencing tree growth. It is typically expressed as the average height of the dominant and codominant trees at a standard base age (Yancey, 2020). Traditionally, site index has been derived by measuring dominant tree height and stand age in the field

and then modelling the height-age relationship using parametric and non-parametric statistical growth functions (Li et al., 2020; Sabatia and Burkhardt, 2014; Tompalski et al., 2015). Dominant tree height is measured as the tallest tree in a plot, and stand age is typically determined by extracting an increment core at diameter breast height and counting the annual growth rings to the pith. The guide curve method is widely used when remeasurements or stem analysis data are not available. The site index guide curve shows the relationship between height and age for dominant and co-dominant trees in a given site condition. This curve serves as the basis for generating anamorphic curves that describe various site classes (Biging, 1985). However, advancements in

* Corresponding author.

E-mail addresses: soniasharma07@vt.edu (S. Sharma Banjade), wynne@vt.edu (R.H. Wynne), thomasv@vt.edu (V.A. Thomas), pcgreen7@vt.edu (P.C. Green), todd.schroeder@usda.gov (T.A. Schroeder).

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remote sensing approaches enable the site index guide curve development using LiDAR (ALS, ICESat-2) for height estimates and time-series optical imagery (Landsat, Sentinel) for age estimates, providing a more efficient and scalable approach (Gopalakrishnan et al., 2019).

While these methods have been reliable, field-based methods have limitations, especially when dealing with extensive geographical areas. Conventional field data collection for measuring site index is time-limited, cost-prohibitive, and labor-intensive. Additionally, field measurements may not provide the spatial specificity required for comprehensive forest management strategies (Eid et al., 2004). Field measurements are inherently localized and may not capture the full extent of a forested area. Old measurements may become outdated and do not accurately represent the current growing conditions, especially in dynamic ecosystems where environmental conditions change over time. This lack of up-to-date and spatially comprehensive data can hinder effective forest management decision-making.

Recent advancements in remote sensing technology, like airborne laser scanning (ALS) and earth resource satellite imaging, have enabled broad-scale estimation of forest attributes, including tree height and age, over vast areas with repeatable and consistent observations on a global scale (Oh et al., 2022). The forest productivity maps that can be generated through remotely sensed data have enhanced spatial resolution and cover large geographical areas for the continuous monitoring of forest productivity.

Tompalski et al. (2015) used ALS and Landsat time series to predict forest productivity in Canada, while Huang et al. (2017) used Landsat and FIA data to map site index in California. Additionally, Véga and St-Onge (2009) utilized photo imagery and canopy height models from ALS to map site index in Quebec. Likewise, studies have focused on generating site index maps in the southern yellow pines using field and remotely sensed ALS data (Gopalakrishnan et al., 2019). Despite its effectiveness in measuring forest structure and topography, ALS has several challenges when applying it to large or heterogeneous regions. While freely available ALS datasets, especially in the United States, have increased accessibility, ALS data are not available globally, limiting their use for large-scale forest monitoring (Vatandaslar et al., 2023). Variations in data quality and coverage due to the data acquisition process, temporal resolution, and sampling density in ALS (Wang et al., 2019) can hinder the creation of reliable site index maps, particularly when confronted with diverse land management practices, tree species, and age classes. ICESat-2 offers a consistent dataset for large-scale applications (Neuenschwander et al., 2020). ICESat-2 also provides near-global coverage and higher along-track spatial resolution due to its photon-counting lidar system, which enhances its capability to detect fine-scale variations in vegetation height. Compared to GEDI, which is limited to latitudes between 51.6°N and 51.65°S, ICESat-2 covers a much broader range, from 88°N to 88°S (Dubayah et al., 2020). Additionally, ICESat-2's finer sampling density enables improved canopy height estimation in sparse forests, where GEDI waveform lidar may have limitations (Zhu et al., 2023).

Stand age is a fundamental factor for site index determination, but it presents challenges, especially over extensive areas. The process of manually measuring individual tree ages is resource-intensive and time-consuming; also, standardized planting records are often unavailable (Packalén et al., 2011; Wulder et al., 2010). Nevertheless, predictions of forest ages can be made by analyzing annual time series of Landsat imagery allows for detecting and mapping stand-replacing disturbances, including their spatial location and timing (Li et al., 2014; Maltman et al., 2023; Schroeder et al., 2011). This process often relies on evaluating the changes in spectral trajectories (Huang et al., 2010; Thomas et al., 2021). The time elapsed since a disturbance can then serve as the age of the forest at that location (Pan et al., 2011). In addition, when combined with other spectral information, these time series data can be used to identify stands of planted pine trees (Fagan et al., 2018).

To address these limitations, this study aims to evaluate the potential of integrating spaceborne LiDAR data and Landsat-derived disturbance

products for estimating forest productivity across actively managed pine plantations in the southeastern United States. Specifically, the objectives of this study are to:

1. Evaluate the agreement between ICESat-2 ATL08 canopy height metrics and ALS measurements
2. Characterize the relationship between canopy height and stand age for actively managed pine plantations using ICESat-2 and Landsat-derived disturbance
3. Develop a regional site index guide curve and compare it with the site index derived from FIA plot data

Based on these objectives, the following research questions were addressed:

1. Are the canopy relative heights in ICESat-2 segments similar to those determined using discrete-return airborne laser scanning data?
2. What is the distribution of heights by age across actively managed pine stands in the southeastern United States?
3. How does the average site index for actively managed pine stands derived using ICESat-2 and Landsat data compare to the site index derived using FIA data in the southeastern United States?

2. Methods

2.1. Study area

The study area is defined by the historic natural range of *Pinus taeda* (loblolly pine) as defined by Little Jr. (1971), which includes parts of 14 states extending through southern New Jersey to central Florida and from eastern Texas to the Appalachian Highlands (Fig. 1). While loblolly pines are predominant in the region, the area is also a habitat for other southern pines, including *Pinus palustris* (longleaf pine), *Pinus echinata* (shortleaf pine), and *Pinus elliotii* (slash pine). The region covers several geographical provinces, including the Atlantic Plain, the Piedmont Plateau, the southern extremities of the Cumberland Plateau, the Highland Rim, and the Valley and Ridge provinces. Humid and warm temperatures with long, hot summers and mild winters characterize the climate in this region. The average annual rainfall ranges from 1020 to 1520 mm, while the mean annual temperature varies between 13°C - 15°C. The dominant soil type within southern pine forests is Ultisols (Baker and Langdon, 1990).

2.2. Data

This analysis uses height information derived from spaceborne lidar (specifically, the ICESat-2 ATL08 product) and derived products describing forest change based on multitemporal Landsat data from 1984 to the present. The ICESat-2 ATL08 product provides heights and is central to this research. The derived products include the U.S. Forest Service Landscape Change Monitoring System (LCMS) Fast Loss Product and a map depicting the location of plantations from 1987 to 2019 (Thomas et al., 2021). ICESat-2 canopy heights were used with age derived from the LCMS Fast Loss disturbance year to find the relationship between the age and height of the southern pine stands in the southeastern region.

2.2.1. ICESat-2-ATL08 canopy heights – general data description

ICESat-2 was launched on 15 September 2018 with a single instrument called the Advanced Topographic Laser Altimeter System (ATLAS) (Zwally et al., 2002) and provides global measurements of vegetation canopy height. We used the Land and Vegetation Height data product (ATL08), version 4, to obtain tree height metrics above the WGS84 ellipsoid for this research. It provides along-track ground and canopy surface heights. Over the vegetated areas in the mid-latitudes, ICESat-2 uses an operational off-nadir-pointing strategy to increase the spatial

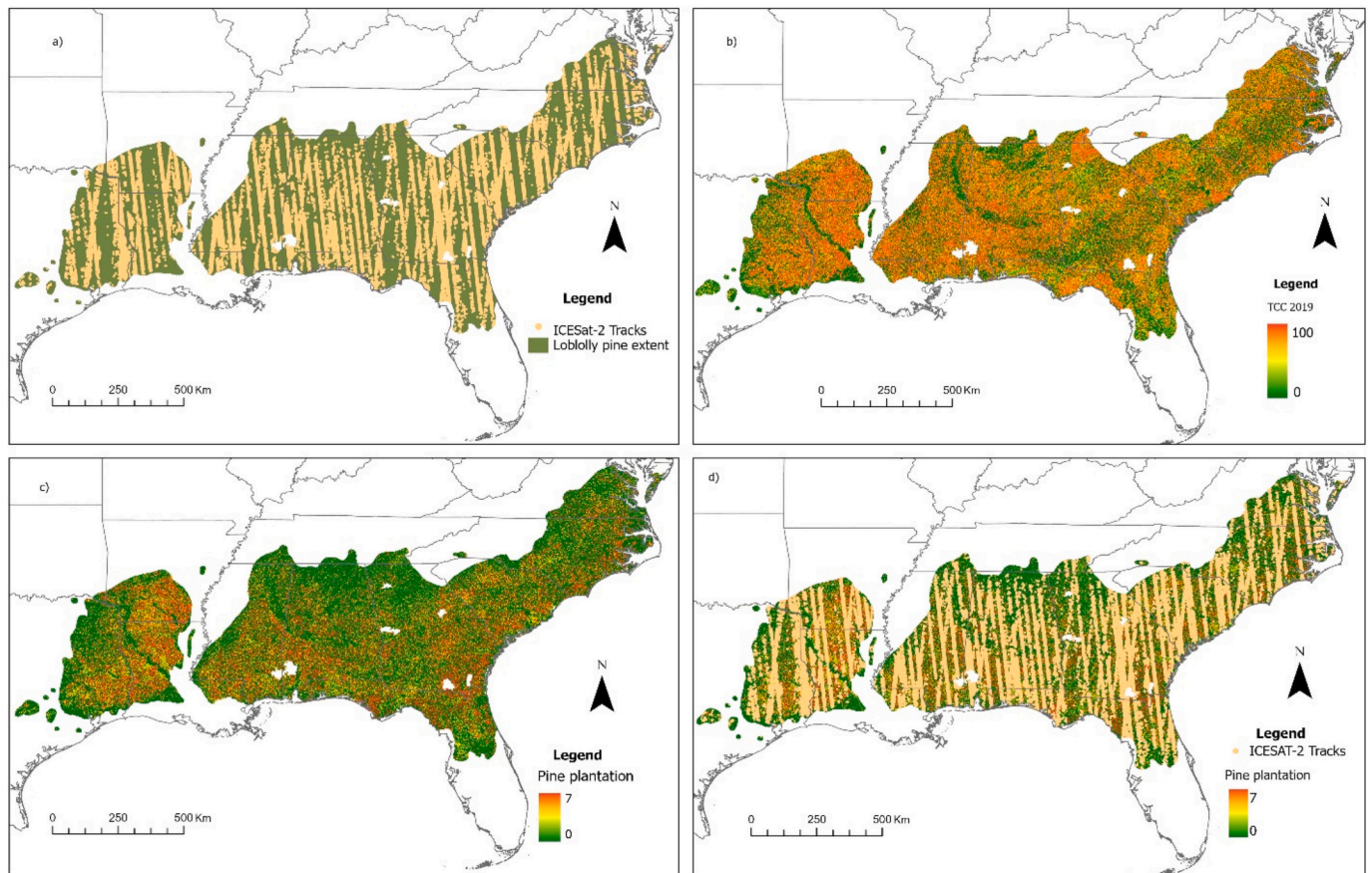


Fig. 1. Spatial distribution of loblolly pines, tree canopy cover, and pine plantations in the southeastern U.S. (a) The green shaded area shows the natural, historic loblolly pines range as defined by [Little Jr. \(1971\)](#) with ICESat-2 tracks. (b) NLCD Database Tree Canopy Cover (TCC) for 2019. (c) Pine plantations map ([Thomas et al., 2021](#)) showing the distribution of southern yellow pines with management intensities applied to these stands. (d) Pine plantations map overlaid with ICESat-2 tracks used for this study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sampling density, resulting in few intentional repeat tracks ([Abdalati et al., 2010](#); [Markus et al., 2017](#); [Neuenschwander et al., 2020](#)). An example of point clouds classified by the ATL08 algorithm is shown in [Fig. 2](#), in Georgia for southern yellow pines.

ATL08 provides canopy height metrics derived from classified photons using a fixed 100 m processing segment along the track. These

include estimates of relative canopy heights (rh) and terrain elevation statistics ([Li et al., 2020](#)). The main challenge for the algorithm is the impact of solar background noise, which makes it difficult to determine the top-of-canopy photons. Therefore, it is recommended to use the rh98 as a measurement of the top of the canopy, as it is less affected by signal-to-noise ratio uncertainty at the top of the canopy ([Malambo and](#)

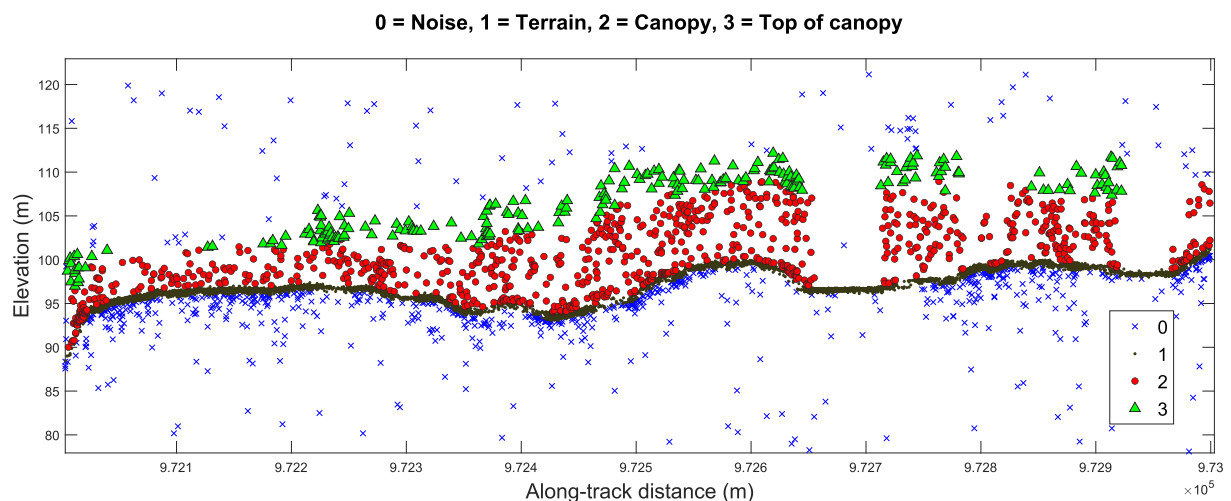


Fig. 2. The figure shows the labeled photons classified by the ATL08 algorithm. The black points represent the ground surface. The green triangles are the top of the canopy determined by the upper canopy surface spline. The red dots are the canopy photons situated between the top of the canopy and the ground surface. The blue x's represent the noise. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Popescu, 2021; Neuenschwander et al., 2019; Popescu et al., 2018).

To process ICESat-2 data, we first obtained all ATL08 files for 2019 through the NASA EarthData website (<https://search.earthdata.nasa.gov>) for the southeastern US. We extracted the following metrics for each segment: *h_canopy*, *h_canopy_uncertainty*, *night_flag*, *latitude*, and *longitude* (Table 1). ICESat-2 data for the southeastern U.S., prior to our data reduction processing, included 10,817 files in hierarchical data format (HDF5), requiring approximately 250 GB of data storage.

Some additional filtering was done to remove segments with unrealistic heights exceeding the highest possible heights of southern pines (but which may represent an anthropogenic feature). All segments with height observations greater than 60 m were excluded (1470 segments).

2.2.2. Land change monitoring system (LCMS) product

The Land Change Monitoring System uses a remote sensing-based dense time series to monitor continuous changes in vegetation and other classes across the conterminous United States and southeastern Alaska from 1985 to the present. It was developed by the United States Department of Agriculture Forest Service (USFS). It was developed using Collection 1 Tier 1 Landsat 4,5,7, and 8 and Sentinel-2a and -2b level 1C top-of-atmosphere reflectance data as predictor layers for modelling (United States Forest Service, 2026). The LandTrendR (Kennedy et al., 2010) and Continuous Change Detection and Classification (Oliver and Webster, 1990; Zhu and Woodcock, 2014) algorithms are used for temporal segmentation of the composites derived from predictor layers. Further, a random forest model is employed to produce change detection, land use, and land cover class products. We used the fast loss year product, which provides the year of LCMS modeled change classes for stand-replacing disturbances (e.g., clear-cutting) and non-stand-replacing disturbances (thinning, damage by fire, wind, and ice) (Housman et al., 2022). The reported year of disturbance can be used as a proxy for the age of pine stands by subtracting the disturbance year from the reference date. Each pixel in the LCMS Fast Loss product represents the disturbance year from 1985 to the present. Cohen et al. (2020) reported a 95% disturbance accuracy for the precursor algorithm, though data product replacements have been designed to substantially improve the detection accuracy, particularly for Fast Loss (U.S. Department of Agriculture, Forest Service, 2023). The LCMS data product was acquired from the USDA Forest Service LCMS Viewer (<https://apps.fs.usda.gov/lcms-viewer/home.html#download>).

2.2.3. Pine plantations map

We used an active forest management map described by Thomas et al. (2021) to identify the pine stands and management intensities. This dataset is a classification of areas that are (or were) pine plantations at some point between 1987 and 2019, as well as an indicator of management level (i.e., non-managed, extensively managed, and actively managed). The overall accuracy of plantation versus non-plantation is 82% (Thomas et al., 2021). With respect to management gradients, the primary class is the 'actively managed plantations,' which includes areas that have been thinned and repeatedly harvested in that period, with a class accuracy of 90%. The largest source of error in this map comes

Table 1
Definition of metrics extracted from ICESat-2 ATL08 products (Neuenschwander and Pitts, 2019).

Metric	Definition
<i>h_canopy</i>	98th percentile of height of all the individual canopy relative heights above ground for the 100 m segment
<i>h_canopy_uncertainty</i>	Uncertainty related to relative canopy heights incorporating all systematic uncertainties, as well as uncertainty from errors of photons
<i>night_flag</i>	Flag indicating data were acquired at night; 0 indicates day, and 1 indicates night.
<i>latitude</i>	Latitude for the center-most signal within each segment
<i>longitude</i>	Longitude for center-most signal within each segment

from stands which are extensively managed and do not follow a characteristic harvesting pattern. Overall accuracy, including management gradients, is 72%. We used this product to constrain our ICESat-2 samples to actively managed stands to ensure structural and biological consistency in the age-height relationship modelling. Actively managed plantations in the southeastern US are typically established after a stand-replacing disturbance and consist of even-aged stands, which reduces structural heterogeneity.

2.2.4. Airborne laser scanning (ALS)

We accessed over 2000 tiles (1 km²) of high-density airborne lidar data (8 points/m²) from the USGS 3-DEP Lidar Data Exploration Tool (<https://apps.nationalmap.gov/lidar-explorer/#/>). Specifically, we used the CPRA LADOTD Lidar 2019 mission, conducted from March 27, 2019, to November 04, 2019. The LiDAR data was collected at a flying height of 9100 ft. using a Leica ALS 80 sensor. The root mean square error (RMSE) in the vertical dimension is 10 cm for Q1 LiDAR point clouds (United States Geological Survey, 2023), which is lower than the error in canopy height for the ICESat-2 ATL08 product. Tiwari and Narine (2022) reported canopy height RMSE values of approximately 6 m when ICESat-2 estimates were compared with ALS in the southeastern region of the US. Hence, this can serve as the base for the quality assurance of ICESat-2 heights.

2.2.5. Forest Inventory and Analysis (FIA)

The Forest Inventory and Analysis Program assesses vegetational attributes in permanent plots on forested lands throughout the United States. The plot sizes and tree species measurement process are consistent and standardized nationwide. These plots are measured every 5 to 10 years. For the FIA plots, tree height was determined by the tallest measured tree in each plot. Tree age is estimated by extracting an increment core at the diameter breast height (DBH) and counting the annual rings to the pith. For each FIA plot, a dominant or codominant site tree is selected, and annual rings are counted for the estimation of the age of the trees (U.S. Forest Service, 2024, Section 2.5.14). The data for our research were acquired from the FIA database (<https://apps.fs.usda.gov/fiadb-api/evaluator>).

2.3. Data processing and analysis

The overall workflow of the study is shown in the flowchart in Fig. 3, and each major step is described below in subsections.

2.3.1. Developing a height, age, and management dataset for pines

To develop height, age, and management datasets, we integrated ICESat-2-derived canopy height metrics with the LCMS Fast Loss product and pine plantation map data using the R (version 4.1.1) programming language. Specifically, we used the packages *rgdal* (version 1.5–32), *sp* (version 1.5–0), and *raster* (3.6–3) to process the spatial data. We used the latitude and longitude metrics to intersect with the LCMS Fast Loss product to extract the year of major disturbance, assuming this represents the establishment year for managed stands. We performed spatial co-location using the center coordinate of each 100 m ATL08 segment to extract the corresponding LCMS pixel. The most recent disturbance year from the LCMS disturbance layer was assigned following the LCMS summary method (Housman et al., 2022). When multiple disturbance years were possible within the ATL08 segment extent, the latest year was used, as it most accurately reflects the chances of the last disturbance event that can influence the canopy height measured by ICESat-2. Since our data acquisition year for ICESat-2 was 2019, we used the LCMS Fast Loss disturbance years from 1985 to 2019 to derive the age of the stands. The extracted forest disturbance year was subtracted from the ICESat-2 data acquisition year to calculate the age of the stands at the time of lidar acquisition. Since the LCMS product contains all forests (including deciduous species), we further intersected the dataset with the pine plantation map to extract actively managed

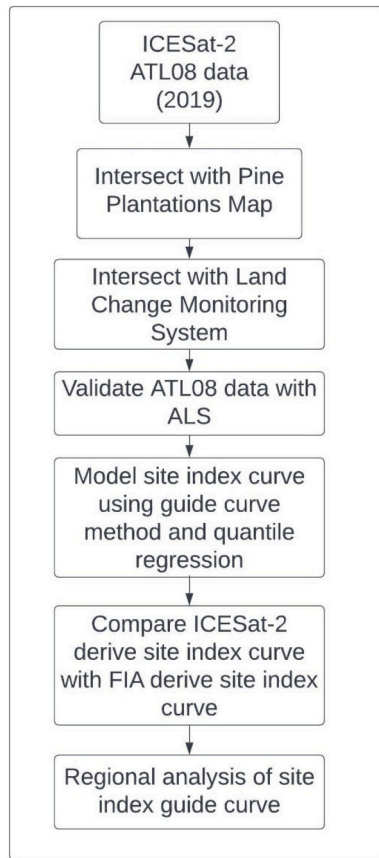


Fig. 3. Flowchart showing the methods involved in the study.

stands that undergo a repeated pattern of harvest and thinning (137,998 segments).

2.3.2. Validation of ICESat-2 ATL08 heights using ALS point clouds

Site index estimation depends directly on the accuracy of canopy height measurements; we conducted an independent validation of ICESat-2 ATL08 heights using ALS data. This validation step was necessary to assess whether ICESat-2 heights were sufficiently reliable for modelling the age-height relationship of southern yellow pines.

For the ICESat-2 ATL08 metrics, processing was done using the *icepyx* package (Scheick et al., 2019) in Python 3.9 (Van Rossum and Drake, 2009), which was created for processing the HDF5 files of ICESat-2. Metrics were extracted from the binary HDF5 format and stored in CSV files while maintaining an identifier to the original file (Table 1). We then removed daytime data (i.e., *night_flag* = 0) to avoid known issues with solar background noise in the strong beams (Liu et al., 2021; Popescu et al., 2018). We also used the *h_canopy_uncertainty* flag to remove invalid data (flag = 3.4028E+38). This flag considers all possible sources of systematic uncertainty, such as timing, geolocation, orbits, and many more, as well as uncertainty in photon classification. A value of 3.4028E+38 is reported if the proportion of ground photons in an ICESat-2 segment is less than or equal to 5% of the total signal photons per 100 m segment. The computed terrain height will likely have low confidence if there are too few ground photons in a section. Since segments with too few ground photons could not give precise measurements of topography and canopy height, segments with an ‘invalid’ value in the canopy height uncertainty index are removed for this study. After these filtering steps, we had 2360 files of ICESat-2 segments for further processing.

To develop a dataset of ALS heights, we accessed over 2000 tiles (1 km²) and selected 80 tiles that overlapped with ICESat-2 footprints for validation. We used the *lidR* package in R (Rousset et al., 2020) to

process “*laz*” files downloaded from USGS LiDAR explorer to generate normalized canopy height models for each tile. First, ground returns (pre-classified by USGS) were used to create a 1 m digital surface model (DSM) using a TIN interpolator using an algorithm, *dsm_point2raster* Digital Surface Model Algorithm in R. The ground elevation was then subtracted from every lidar point to create a ground-normalized canopy height dataset. The canopy surface was interpolated using the *rasterize* algorithm to generate a 1 m canopy height grid.

To approximate the footprint of the ICESat-2 segment on the ground, we created a 100 × 13 m bounding box around the center coordinate of each segment to sample our 1 m cells, following Neuenschwander et al. (2020). We then extracted the 98th percentile of heights within this footprint, represented by the approximately 1300 ALS grid cells per segment. We also determined the dominant land cover by intersecting this box with the National Land Cover Dataset (NLCD) and extracting the model. We used the Python packages *gdal*, *pandas*, and *numpy* to directly compare the heights across the land covers in the 80 tiles.

To assess the agreement between the two height products, we fit the following model using Ordinary Least Squares (OLS):

$$IS2heights = b_0 + b_1 \times ALS + \varepsilon$$

where,

IS2heights = ICESat-2 derived heights of southern yellow pines.

ALS = Airborne laser scanning heights.

b_0 = intercept.

b_1 = slope representing a relationship between ICESat-2 and ALS heights.

ε = error term and calculated the percent of the dataset within the 95% confidence interval, the RMSE and R^2 of the fit, and the mean absolute deviation.

2.3.3. Generating a site index guide curve for actively managed stands and the regional distribution of site indices

We used the Schumacher (1939) model to generate the site index guide curve using ICESat-2 ATL08 segments as the unit of analysis. Unlike models that assume constant growth elasticity, this model accounts for variable elasticity, reflecting the biological reality of rapid growth followed by gradual slowdown as trees mature (Nanang and Nunifu, 1999). It incorporates asymptotic convergence, ensuring the height growth approach biological maximum over time, which helps reduce biases in site index estimates caused by uneven site quality across various age classes, particularly when remeasured permanent plots are unavailable (Cailliez and Alder, 1980; Walters et al., 1989). Our choice of this model was also motivated by its simplicity, ease of fitting, and widespread use in forest modelling when height-age pairs are available. To have an age-height relationship using the logarithm of height and the reciprocal of age, we used the following equation:

$$\ln(h_{dom}) = b_0 + b_1 (a^{-1}) \quad (1)$$

where,

$\ln(h_{dom})$ = logarithm of dominant height.

a = age of the stands.

This model was used to generate a site index guide curve for the actively managed pine stands in the southeast, which included 137,998 ICESat-2 segments. Initial analysis revealed significant challenges associated with the miscalculation of age for some stands that have been heavily thinned. Since stand age was calculated as the ICESat-2 data acquisition year minus the forest disturbance year, heavy thins identified as fast loss resulted in many noisy data (60,336 segments) that were far too tall for their age. To address this issue, we adjusted the “*change_raw_probability_fastloss*” band of the LCMS by setting the probability threshold to 70%. The noise was reduced, but the challenge of having heavy thins identified as “Fast Loss” persisted. Higher probability thresholds also caused a change in the identified Fast Loss year, with

apparent increases in the preponderance of more recent disturbances.

Hence, we adopted a quantile regression approach to address the issue of anomalously high heights of ATL08 metrics recorded at younger ages in our dataset. Specifically, we used the 99th percentile and 1st percentile as thresholds to filter out noise using region-wide, long-term measured ground plot data as a reference provided by the Forest Modelling Research Cooperative (FMRC) at Virginia Tech (<https://fmrc.frec.vt.edu/>). These data represent operational management and site quality across the native range of loblolly pine. Quantile regression is well-suited for datasets with discrepancies, as it focuses on specific quantiles rather than the mean, making it robust to noisy data. Traditional least squares regression can be biased by such noisy data, leading to unreliable parameter estimates fit for the site index guide curve. By contrast, quantile regression estimates multiple percentiles, capturing the variability in canopy heights across the age classes.

We employed the following model to derive the 99th and 1st percentile height filters:

$$H(p, \text{age}) = H_{\max} * (1 - e^{-\alpha * \text{age}})^{\beta} \quad (\text{where,})$$

p = desired percentile (99th or 1st).

age = age of the tree stands.

α and β are the parameters.

For 99th percentile $H_{\max}$ was set to be 45.7 m and 14.6 m for the 1st percentile based on observed tree height data from FMRC.

Further, we conducted a regional analysis by intersecting the derived dataset with two physiographic regions of the USA at the province level: Coastal Plain (113,369) and Piedmont (14,679). We applied the same quantile regression percentiles (0.99 and 0.01) with the Schumacher (1939) model to derive the fitted site index guide curve.

2.3.4. Comparison of ICESat-2-derived site index with FIA-derived site index

We compared our results with a trusted independent dataset (FIA). We used the maximum height (MaxofHT) and stand age (STDAGE) of southern yellow pines of the most recent cycle of annual FIA plots in the southeastern region. The data included one observation for each plot location, 601 samples in total. We then used linear regression to develop a site index guide curve for direct comparison to the ICESat-2 derived curve.

We conducted the Cramér-von Mises test to assess the agreement between the ICESat-2- and FIA-derived site index guide curves. The Cramér-von Mises test is a goodness-of-fit test that evaluates the similarity of two cumulative distribution functions (Darling, 1957). The null hypothesis is that the samples are drawn from the same distribution. The “twosamples” package (version 2.0.1) in R was used to conduct the test.

3. Results

3.1. Statistical summary of the heights dataset for actively managed pine stands

The statistical summary of processed ATL08 heights for 25-year-old

Table 2
Statistical summary of ATL08 heights of age 25 for actively managed pine stands. The given heights are in meters (m).

Summary	Statistics
Count	1987
Mean	20.1
Standard deviation	4.7
Minimum	2.2
25%	18.0
50%	20.4
75%	22.5
Maximum	55.3

southern yellow pines in the southeastern region is in the table below (Table 2). A total of 1987 segments were taken for the age of 25 years, which showed a central tendency around 20.1 m. Most of the trees at 25 years fall within the range of 18.0 m to 22.5 m.

Further, for the initial exploration of height distribution across the region, these segments are shown in a histogram (Fig. 4). This helps to understand the variability and typical height ranges within the managed forest stands, potentially influenced by factors such as management practices. The x-axis represents the ATL08 canopy height, ranging from 0 m – 60 m, and the y-axis represents the frequency of occurrence of each height range. The tree heights show notable peaks between 10 m and 30 m, indicating that most trees are distributed in this range.

The histogram of canopy heights at the base age of 25 years demonstrates a normal distribution across the region.

3.2. Validation of ICESat-2 ATL08 heights using ALS point clouds

The linear fit (Fig. 5) between ICESat-2 ATL08 98th percentile heights and ALS 98th percentile heights showed that the heights were strongly correlated, with an R^2 of 0.90. According to the NLCD classification, multiple land cover classes were present, with the majority being evergreen (coniferous), woody wetlands, and grassland/herbaceous.

The average difference between ALS and ICESat-2 ATL08 heights is about 1.4 m, and the RMSE is 2.2 m (Table 3).

Fig. 6 represents the residual plot showing predicted values versus residuals. The spread of the residual seems symmetrical, mostly around zero. While the spread of the residuals is largely symmetrical, ATL08 substantially under-predicts ALS-derived heights in some instances.

3.3. Height by age for southern yellow pines

Fig. 7 represents the ATL08 height (y-axis) distribution for each age (x-axis) category from 1 year to 33 years for actively managed southern yellow pines. A distinct trend in the violin plots is the accelerated growth rate in the younger stands. As tree age increases, the height variations stabilize, suggesting the older stands tend to have more consistent height distributions. The older stands, comparatively, had a higher density than the younger stands. The presence of noisy data presented within the red bounding box in the younger stands is likely caused primarily by commercial thinning, which confounds our approach to estimating age. The thinning disturbance can be seen in the Fast Loss product. In our estimation of age, this has the effect of setting the thinning year to “Age = 0”, which is incorrect, as only a portion of the trees were removed.

3.4. Site index guide curve and spatial distribution

We generated the following regression coefficients for our site index equation:

$$\ln(h_{\text{dom}}) = 3.3 - 7.68(a^{-1}) \quad (2)$$

The curve fit had an $R^2 = 0.78$ and RMSE = 2.6 m (Fig. 8). The data has been filtered to include 1st and 99th percentile heights based on field data, ensuring that the extreme outliers are excluded from the analysis.

The site index at a base age of 25 years is 19.9 m (Fig. 8) derived from ICESat-2 canopy heights and Landsat ages, meaning that the dominant and co-dominant trees are expected to reach 19.9 m height when they are 25 years old. The result shows the growth trend of the stands representing the productivity of the site for the southern yellow pines. This analysis, covering heights up to 40 m and ages up to 35 years, is valuable for understanding growth patterns and predicting future growth (Gopalakrishnan et al., 2019). These insights are crucial for effective forest management practices, such as thinning and harvesting, as well as

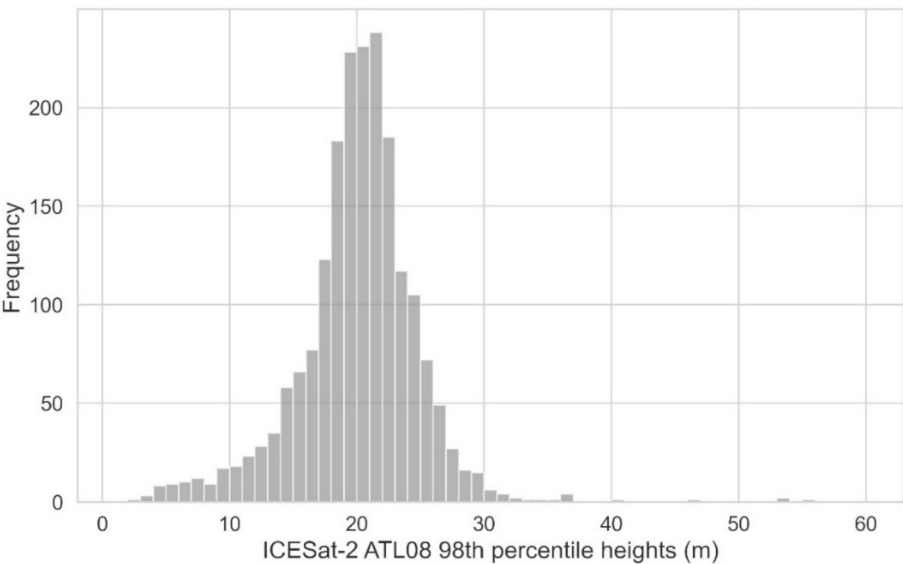


Fig. 4. Histogram of processed ATL08 heights for 25-year-old actively managed stands (1987 segments).

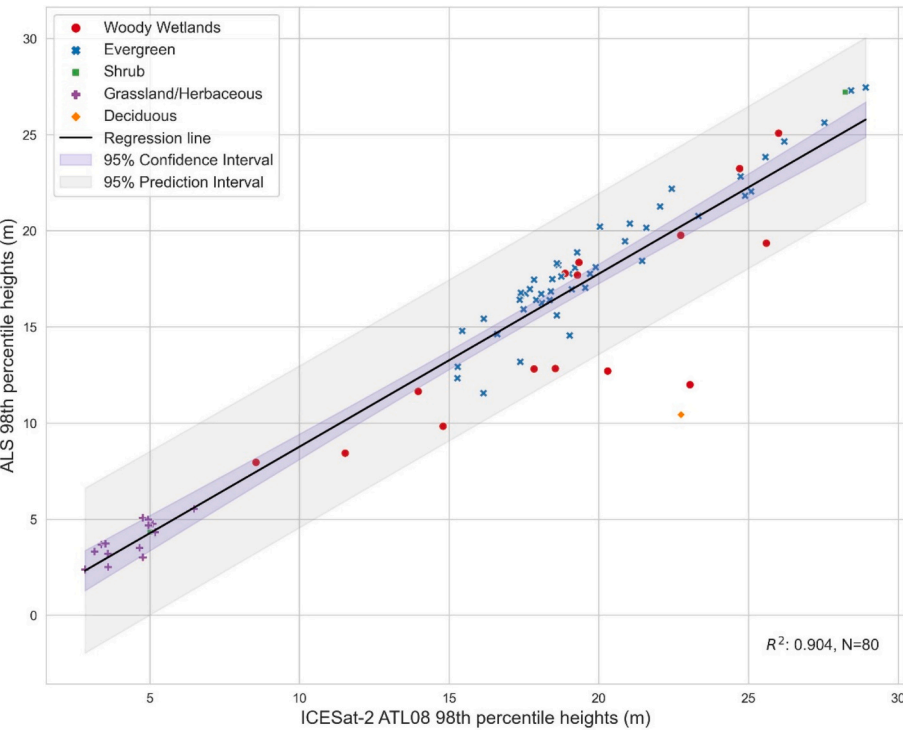


Fig. 5. Linear fit showing the relationship between ICESat-2 ATL08 98th percentile heights in meters with ALS 98th percentile heights in meters. The colour code represents the various NLCD land cover classes that fall within the region of ICESat-2 ATL08 tracks.

Table 3
Statistical value of the comparison of ATL08 heights and ALS point clouds (MAD = Mean absolute deviation).

Condition	Sample size	MAD (m)	RMSE (m)	R ²
ATL08 98th vs ALS 98th	83 segments	1.42	2.18	0.90

ecological research and conservation planning.

For the Coastal Plain, the regression coefficients were $b_0 = 3.3$ and $b_1 = -7.69$. The curve fitted had an R^2 of 0.78. The site index for the Coastal Plain at the base age of 25 years is 19.9 m (Fig. 9), indicating the

dominant and co-dominant trees in this area are expected to have a height of 19.9 m at the age of 25 years in the same climatic conditions.

For Piedmont, the regression coefficients were $b_0 = 3.3$ and $b_1 = -7.40$. The curve fit had an R^2 of 0.77. The site index for the Piedmont region at the base age of 25 years is 20.5 m (Fig. 10), representing the productivity of the Piedmont region. The dominant and co-dominant trees in this region will attain a height of 20.5 m at the age of 25 years under climatic conditions.

Both Fig. 9 and Fig. 10 indicate a fitted site index guide curve that models the forest growth pattern in the Coastal Plain and Piedmont regions. Fig. 11 shows the spatial distribution of site index values at the base age of 25 years across the Coastal Plain and Piedmont regions. The

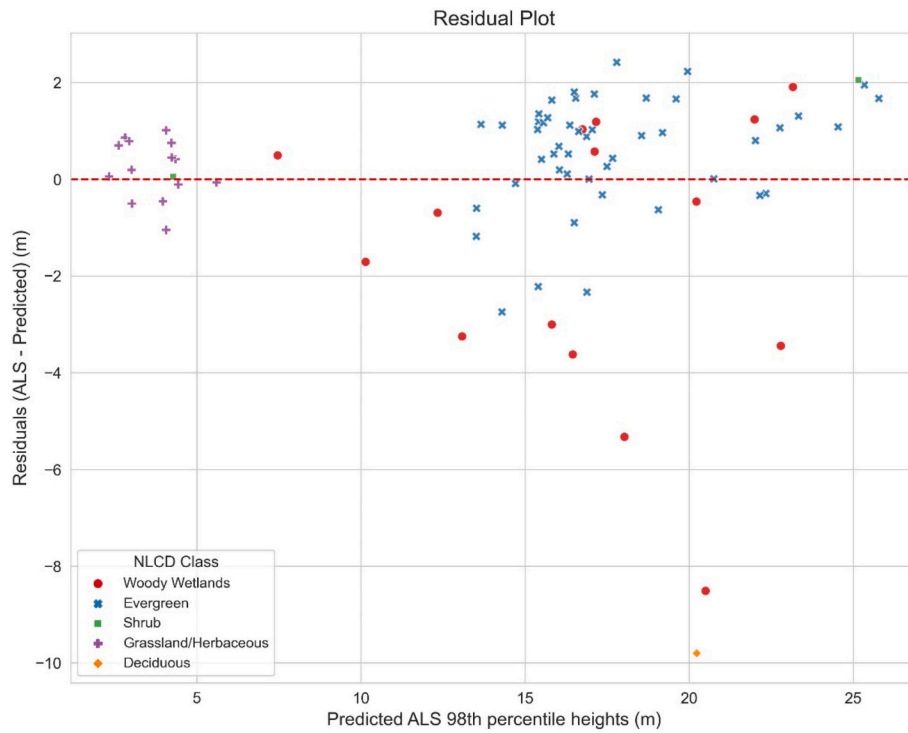


Fig. 6. Residual plot showing predicted values by residuals.

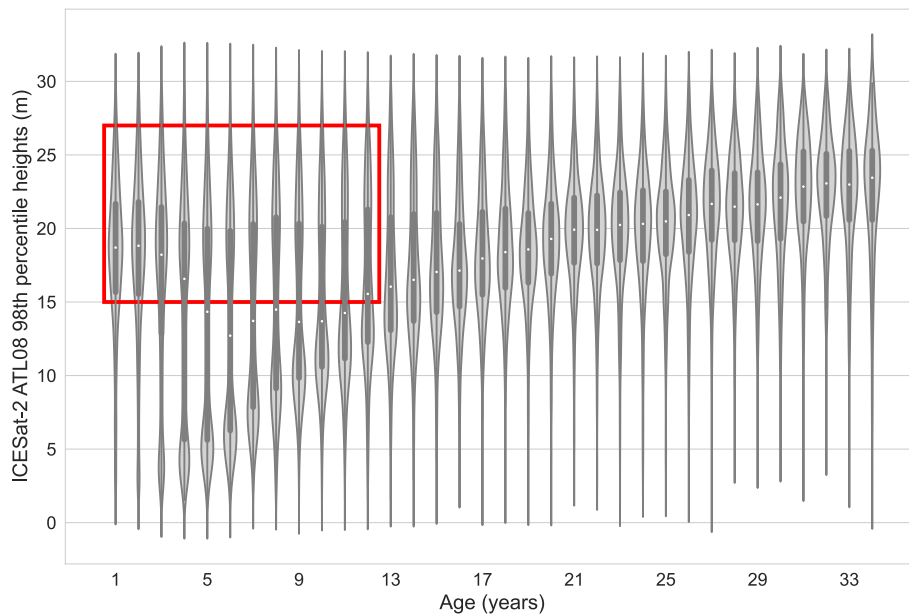


Fig. 7. The violin plot of ICESat-2 ATL08 98th percentiles heights in meters over ages in years for actively managed stands. The red bounding box indicates a portion of the noisy data detected, showing higher heights in the younger stands ranging from 1 to 12 years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

site indices value ranges from 7.5 m to 21.5 m in the Coastal Plain and from 7.8 m to 22.3 m in the Piedmont region. Comparatively, the Piedmont region showed higher productivity, which may be influenced by climatic factors, topography, and soil conditions.

3.5. Comparison of ICESat-2-derived site index with FIA-derived site index

We fitted the FIA data points with the guide curve method using eq. 1

and obtained the following parameters:

$$\ln(h_{dom}) = 3.31 - 8.10(a^{-1}) \quad (3)$$

with $R^2 = 0.83$ and RMSE = 2.51 m. The FIA-derived site index value for base age 25 years was calculated as 19.8 m using ground plot data (compared to 19.9 m for ICESat-2) (Fig. 12).

The data were constrained to a prediction interval between the 1st and 99th percentiles using quantile regression to model a site index curve in FIA data for southern yellow pines. The site index value from

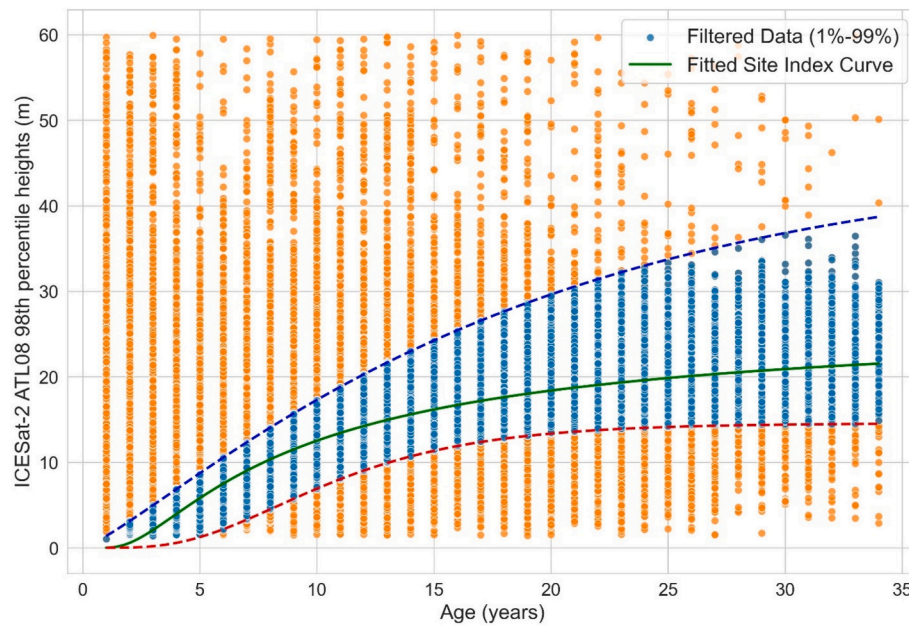


Fig. 8. The green fitted line indicates the site index guide curve generated using ICESat-2 ATL08 heights and Landsat-derived age for the southeastern region using the quantile regression and the [Schumacher \(1939\)](#) model. The blue points are identified as signals (77,662 segments), which fall between the 99th and 1st percentile, and the orange points are identified as noise by the quantile regression filter. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

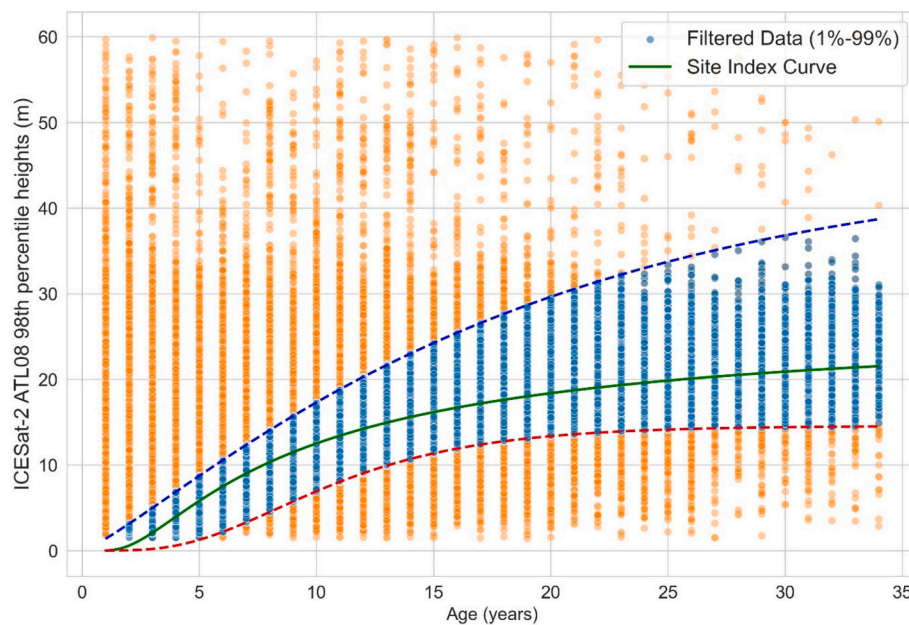


Fig. 9. The green fitted line indicates the site index guide curve generated using ICESat-2 ATL08 heights and Landsat-derived age for the coastal plain physiographic province region using the quantile regression and the [Schumacher \(1939\)](#) model. The blue points are identified as signals (64,569 segments), which fall between the 99th and 1st percentile, and the orange points are identified as noise by the quantile regression filter. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

FIA data indicates that co-dominant and dominant trees would reach a height of 19.8 m at the age of 25 years. Further, the FIA ground plot-derived site index guide curve is compared with the ICESat-2-derived site index guide curve in [Fig. 13](#). There is a strong agreement between the two curves, with the ICESat-2-derived heights being slightly higher at every age.

The Cramér-von Mises test yielded a p-value of 1.00, favoring the null hypothesis that the distributions of site indices derived from both ICESat-2 and FIA are statistically similar. This result suggests a high

degree of agreement between the site index guide curves generated for remote sensing data and ground plot data, indicating that the ICESat-2-derived site index closely matches the FIA-derived site index across the southeastern region.

4. Discussion

The main goal of this study was to determine whether ICESat-2 canopy height metrics combined with Landsat-derived age can be used

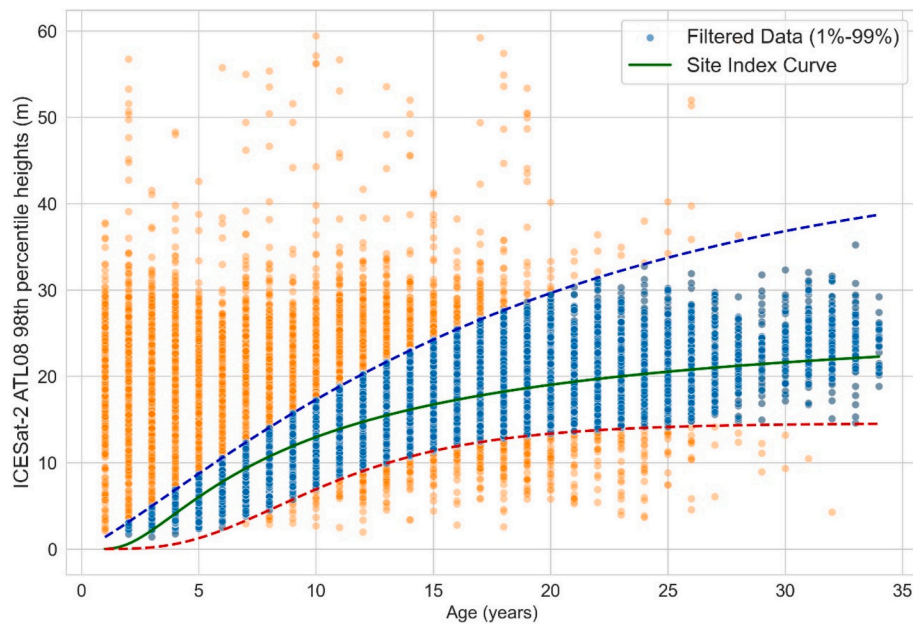


Fig. 10. The green fitted line indicates the site index guide curve generated using ICESat-2 ATL08 heights and Landsat-derived age for the Piedmont physiographic province region using the quantile regression and the Schumacher (1939) model. The blue points are identified as signals (7879 segments) that fall between the 99th and 1st percentile, and the orange points are identified as noise by the quantile regression filter. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

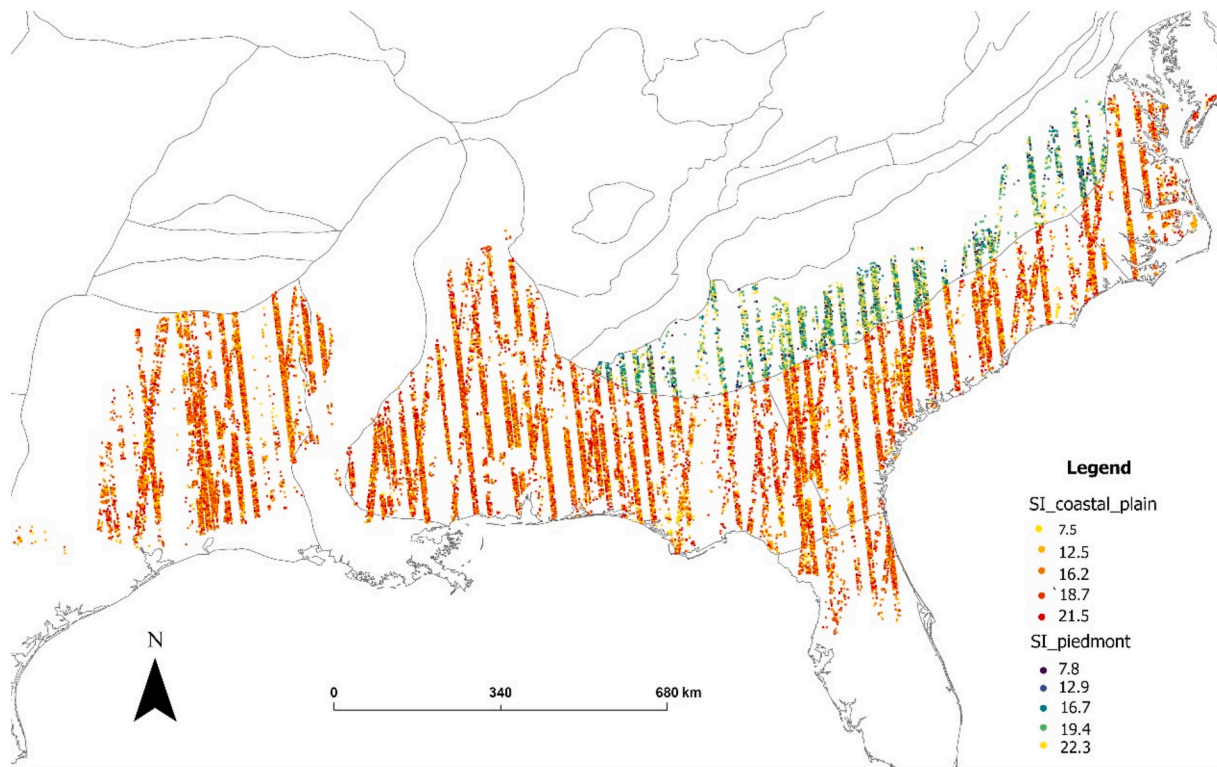


Fig. 11. The orange colour gradations show the site index values in the Coastal Plain ranging from 7.5 m to 21.5 m. The green colour gradations show the site index values in the Piedmont region ranging from 7.8 m to 22.3 m. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to develop a reliable and scalable site index guide curve for southern yellow pines across the southeastern United States. To achieve this, ICESat-2 ATL08 heights were first validated with ALS data, a site index guide curve was then developed using quantile regression, and the results were compared with the FIA-derived site index guide curve. A key

contribution of this work is a regional point map of site index derived from remote sensing that aligns closely with the FIA-derived site index, while covering a much broader geographic area than field plots. The comparison between ICESat-2-derived site indices and FIA-derived site indices was based on 601 samples. Given that the southeastern U.S

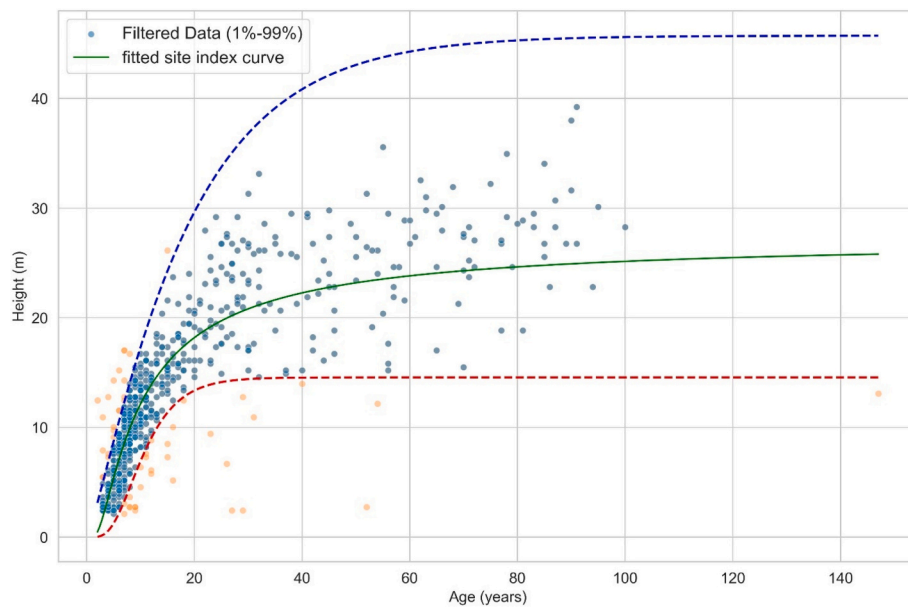


Fig. 12. The green fitted line indicates the site index guide curve generated using FIA plot data for the southeastern region using the quantile regression filter and the Schumacher (1939) model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

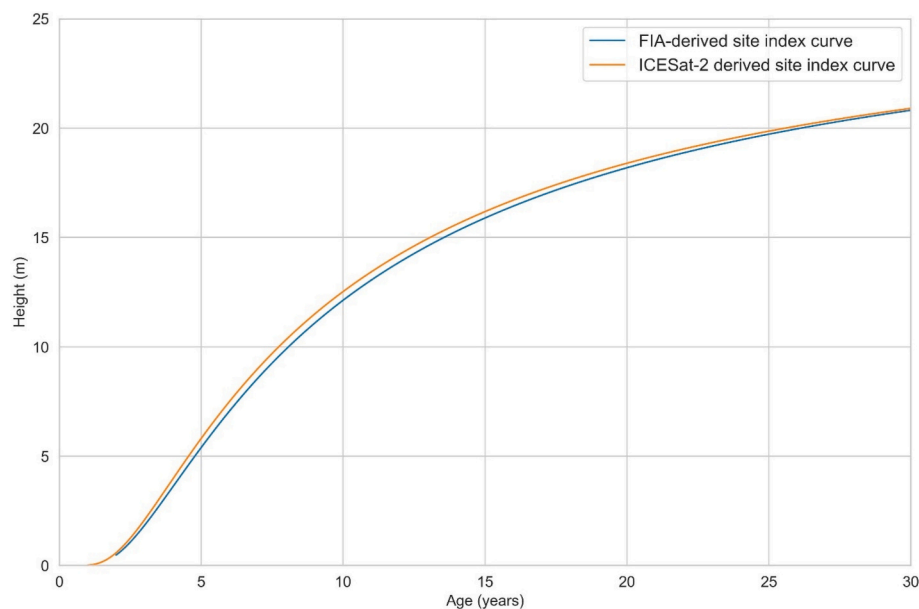


Fig. 13. The blue-colored fitted line indicates the site index guide curve generated using FIA plot data, and the orange-colored line shows the site index guide curve generated by remote sensing data for the southeastern region till age of 30 years of the southern yellow pines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

accounts for a substantial portion of the nation's timber production and hosts one of the most economically significant pine plantations, a scalable and freely reproducible method for tracking forest productivity across this region carries considerable practical value.

Validation of ICESat-2 heights was crucial for having confidence in ICESat-2 canopy heights. Direct validation with field-measured heights is challenging for spaceborne lidars, primarily because the probability of tracks intersecting established field plots at sufficient density tends to be low. To avoid this constraint, we compared our ICESat-2 canopy heights with ALS data. High-density ALS data provided a spatially continuous canopy height reference for this comparison. The comparison showed a strong correlation ($R^2 = 0.90$) and a mean difference of 1.4 m between ICESat-2 rh98 and ALS rh98. These results support the reliability of

ICESat-2 canopy height metrics for further application in deriving the site index guide curve. We used the 98th percentile (rh98) as the canopy height metric following recommendations by Neuenschwander and Pitts (2019), since this percentile emphasizes dominant canopy trees and reduces sensitivity to signal-to-noise uncertainty at the canopy top. ICESat-2 height accuracy has been reported across different forest types and regions with RMSE of 4.3 m in short-stature vegetation (Zhu et al., 2023), and 3.2 m across mixed forest types (Liu et al., 2021). These differences reflect the diversity of stand structures and validation approaches used in those studies. Prior studies have also shown that lidar-derived heights may underestimate field heights (Anderson et al., 2015; Liu et al., 2021; Wang et al., 2019), while ICESat-2 has sometimes overestimated heights in shorter stands (Rai et al., 2024; Moudry

et al., 2022; Liu et al., 2021). In actively managed southern yellow pine, which are structurally more uniform and even-aged, and are found on relatively flat to gently rolling terrain, our within-study validation showed a mean difference of 1.4 m. This suggests ICESat-2 performs well in this forest type and provides a consistent representation of dominant canopy height for site index estimation.

The site index at base age 25 for ICESat-2 (19.9 m) is marginally higher than that of FIA (19.8 m). However, the Cramér-von Mises test (p -value = 1.00) indicates strong agreement between these two datasets, showing the reliability of our methodology for deriving a site index from remote sensing datasets. The marginal difference between these datasets could be due to two different approaches used for deriving the height and age of the pines. The FIA site index is based on maximum tree height measured in plots and age determined from increment cores (U.S. Forest Service, 2024, Section 2.5.14). In contrast, the ICESat-2 approach uses rh98 canopy height metrics and age derived from the Landsat disturbance map. The larger number of ICESat-2 samples compared to spatially limited FIA plots may also smooth local variability, contributing to the slightly higher estimate.

At the physiographic level, differences between the Coastal Plain and Piedmont regions highlight spatial variability in forest productivity. The Piedmont site index (20.5 m) was slightly higher than the Coastal Plain (19.9 m). These variations likely reflect differences in soil conditions, topography, and ecological factors. This aligns with findings by Ribas-Costa et al. (2024), who identified physiographic province as an important driver of site productivity. The wall-to-wall site index map generated in this study makes such regional productivity gradients visible at a scale that field plots alone cannot provide.

While the results are encouraging, several limitations should be considered. Despite the strong correlation between ATL08 heights and ALS, some observations showed underestimation and unexpected extreme values. These limitations could be attributed to noise and the photon cloud processing algorithms of ICESat-2. While ICESat-2 employs a high-frequency micro-pulse laser that generates height values every 0.7 m, it records only 0–4 photons per laser pulse over vegetation (Neuenschwander and Pitts, 2019). This limited photon return can lead to inadequate characterization of forest canopies and an increased possibility of missing canopy tops, resulting in underestimation when compared to ALS data. Active forest management activities, such as thinning and harvesting, are continuously carried out in the study site. The extreme values could be the result of a change in canopy cover with sparse vegetation (Malambo and Popescu, 2021). Additionally, the LCMS disturbance map also misclassified heavy thinning as a stand-replacing disturbance, which led to incorrect age calculation. It also should be noted that our analysis used ATL08 Version 4 data products, and results may vary with subsequent product versions.

Another important consideration is data accessibility and reproducibility. While the FIA data is publicly available, precise FIA plot coordinates are not publicly released, and field plots are sparse (~4 per 100 km²). As a result, comparison to FIA data is constrained to coarse spatial scales. This limitation should be considered when replicating the methods present in this study. In addition to FIA, the Soil Survey Geographic Database (SSURGO) database provides spatially explicit site indices estimated derived from soil characteristics. Although the SSURGO-based site index is model-driven and soil-dependent rather than directly height-age based, it represents another valuable spatial source of productivity information (<https://www.nrcs.usda.gov/resources/data-and-reports/soil-survey-geographic-database-ssurgo>). Future studies could compare ICESat-2 and Landsat-derived site index estimates with the SSURGO-based site index to further evaluate whether remote sensing captures the same productivity gradients that soil properties predict.

Despite these limitations, the broader implication of this study is that ICESat-2 provides consistent, large-scale canopy height measurements that can be integrated with Landsat time-series products to estimate forest productivity across extensive geographic areas. Unlike ALS, which

is spatially limited, ICESat-2 offers continuous landscape sampling at no additional cost. Compared to GEDI, which is restricted to latitudes between 51.6°N and 51.6°S (Dubayah et al., 2020), ICESat-2 provides broader latitudinal coverage, making it more suitable for productivity mapping in regions beyond the southeastern U.S. From a management perspective, the site index map generated in this study enables the identification of areas with lower and higher productivity. Lower productivity regions may benefit from targeted silvicultural interventions, while higher productivity areas may be prioritized for maximizing timber yield or carbon sequestration. The spatially explicit nature of the productivity map also allows sub-regional comparisons and monitoring of long-term changes associated with forest management strategies (Fox et al., 2007), CO₂ fertilization effects (Burkhart and Tomé, 2012; Palmroth et al., 2024), and climate change impacts (Thomas et al., 2018).

Overall, this study demonstrates that ICESat-2-derived canopy heights, when combined with Landsat-derived canopy age, can produce a reliable and scalable site index guide curve that aligns closely with FIA-based estimates. This supports the use of spaceborne lidar as an operational tool for assessing and monitoring forest productivity across large regions.

5. Conclusion

ICESat-2 ATL08 canopy height data were assessed using ALS point clouds, with a lower RMSE than previously reported. Our findings show a close alignment between the ICESat-2 and Landsat-derived site index guide curve and the FIA-derived site index guide curve. The site index map developed for regional analysis provides insights into the influence of climatic and ecological factors on forest productivity.

Quantile regression enabled the construction of a site index guide curve using LCMS-derived ages and ICESat-2 ATL08 heights, even given confusion between stand-replacing disturbances and heavy thins. This research showcases the potential of spaceborne remote sensing to assess and monitor site index over an extensive geographical range. The site index guide curve and productivity map generated from this research have practical implications in forest management and policy making.

CRedit authorship contribution statement

Sonia Sharma Banjade: Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Randolph H. Wynne:** Writing – review & editing, Validation, Methodology, Conceptualization. **Valerie A. Thomas:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Patrick C. Green:** Writing – review & editing, Methodology. **Todd A. Schroeder:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sonia Sharma Banjade reports financial support was provided by USDA Forest Service Southern Research Station. Dr. Randolph H. Wynne, Dr. Valerie A. Thomas reports financial support was provided by USDA McIntire Stennis Program. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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forest” (Number: 20-jv-11330145-037) and a USDA McIntire-Stennis cooperative forestry research program award entitled “Precision forestry for southern-pine carbon monitoring” (Number: VA-136647). Some of the work on this manuscript was performed by U.S. government employees on official time, therefore it is considered in the public domain and not subject to copyright.

Data availability

Data will be made available on request.

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