Modeling stand-level forest attributes using lidar and Common Stand Exam data

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Abstract

Traditional forest inventories provide important information to forest managers regarding stand volume, structure, and species composition. While crucial for making informed decisions, forest inventories can be time intensive, costly, and acquisition can delay forest management actions. In some cases, publicly available and large-scale LiDAR datasets can serve as a means for assisting with or even substituting for pedestrian methods when collecting forest inventory data. This study focuses on the development of a new geospatial methodology and model development where LiDAR data was leveraged to recreate Common Stand Exam (CSE) results. CSE protocols are the U.S. Forest Service's approach to conducting forest inventories, with Live Tree Stocking and Volume reports being major outputs following field data acquisition. Modelling efforts yielded statistically significant similarities in BA, TPA, board-feet volume, and tonnage volume when comparing traditionally acquired CSE data versus LiDAR-based analysis. While lidar-based approaches might not be appropriate for every forest management objective, these results demonstrate that they have the potential to be leveraged in scenarios where major forest metrics are required. This could represent significant time and cost efficiency for forest managers who are confronted with challenging deadlines, fiscal limitations, and harsh environmental conditions.

Keywords: lidar, Common Stand Exam, shortleaf pine, loblolly pine, forest inventory

Introduction

Stand-level forest attribute data is an important resource for managers when making decisions about forest prescriptions and treatments. Forest management often happens at the stand-level or multi stand-level scale but stand inventory and volume data are not always readily available. Its acquisition can be cost and time-prohibitive, with timber cruises requiring significant personnel time in the field.

Alternatives that reduce or eliminate the need for personnel intensive field work have been applied using a variety of methods (Hummel et al., 2011; Brosofske et al., 2014; Hemingway and Opalach, 2024). They typically involve the acquisition of some remote sensing dataset using spaceborne, airborne, or UAV-borne methods, and analyzing that data to model forest attributes. When and where these methods can be applied effectively is highly circumstantial, and depend on factors such as resource availability, budget, and the spatial scale being assessed. For example, a UAV or drone might be a cost-effective option for forest managers with limited resources and budget, but the spatial scale they operate within is relatively small and inadequate for assessing larger areas.

Lidar is often the foundational remote sensing dataset used when recreating forest attributes that characterize structure and species composition (Dubayah et al., 2000; Balestra et al., 2024). Lidar data is comprised of laser pulses from the sensor, or returns, that measure the heights of vegetation and physical features on some terrestrial surface. The resulting point cloud datasets can vary in density and are capable of modeling forest vegetation in precise detail (Sumnall et al., 2021; Ross et al., 2024). This includes modeling species richness and composition of forests using lidar-derived explanatory metrics (Anderson et al., 2021; Wu et al., 2024).

The acquisition of lidar on large scales is one example of a cost prohibitive approach to modeling stand-level forest inventories, but open source lidar datasets create potential opportunities to conduct analysis without incurring those costs. For this study, a 2018 USGS lidar dataset was collected two years prior to a traditional forest inventory conducted on the Sam Houston National Forest in Walker County, Texas, United States. I used this dataset to determine whether a geoprocessing workflow could be developed for recreating stand-level volume, basal area (BA), and trees per acre (TPA) from our Common Stand Exam (CSE) forest inventory. CSE inventory protocols were developed by, and unique to the U.S. Forest Service. I also attempted to separately model shortleaf pine (*Pinus echinata*) volume, which is a dominant overstory species but not as abundant as loblolly pine (*Pinus taeda*) in most areas of our study site.

Methods

2.1 Study area

CSE data was collected in 105 stands within compartments 31-33 on the Sam Houston National Forest (SHNF) in Spring 2020 (Figure 1). The SHNF is located in Walker, Montgomery, and San Jacinto counties of Texas, United States, and is often characterized by mixed loblolly pine and shortleaf pine overstory. The two can vary in their presence and abundance, with shortleaf pine being an upland species and loblolly pine being a ubiquitous species. Major hardwood species include southern red oak (*Quercus falcata*), post oak (*Quercus stellata*), cherrybark oak (*Quercus pagoda*), American sweetgum (*Liquidambar styraciflua*), black tupelo (*Nyssa sylvatica*), and winged elm (*Ulmus alata*). Hardwoods generally represent a small percentage of stand species composition (<15%), with some exceptions on the east, northeast sides of the study site. Soils are mostly characterized by fine sandy loams and loamy fine sands, with some areas of eroded and frequently flooded clay soils to the northeast of the site.

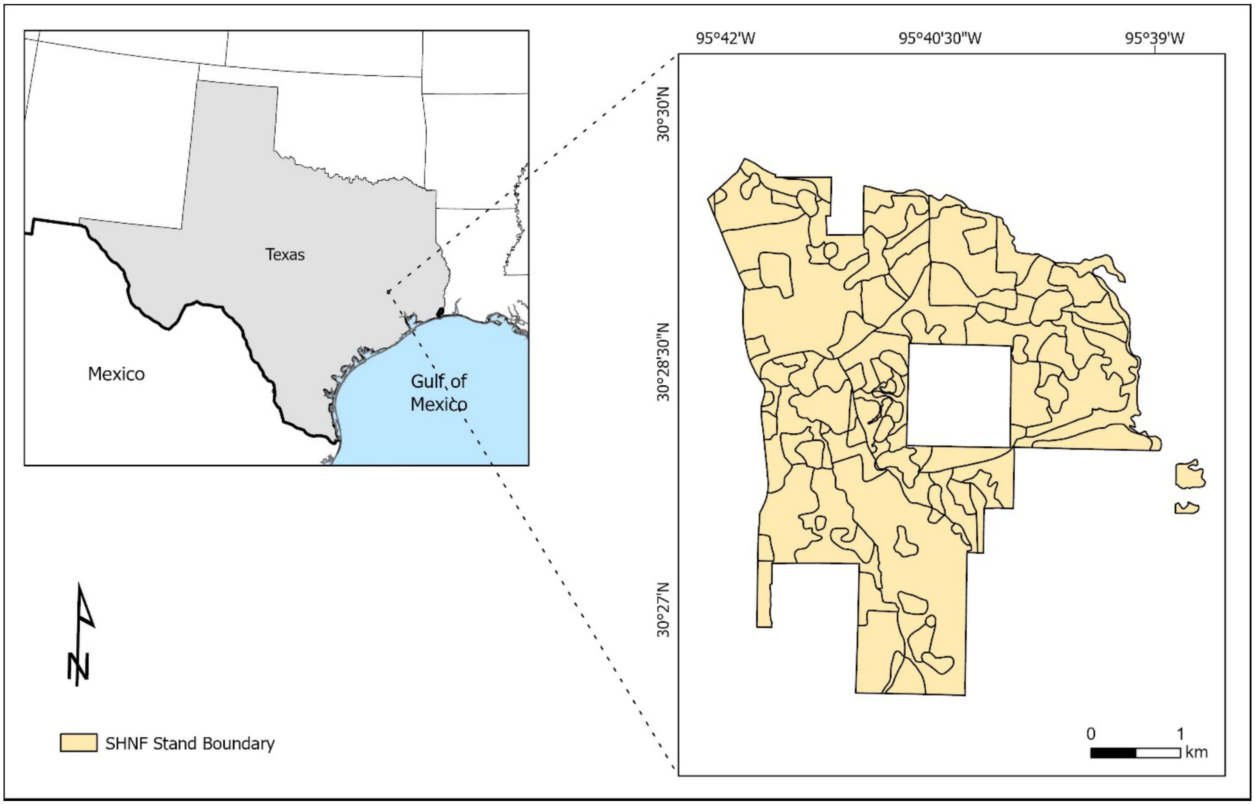

Fig. 1. Stands within Compartments 31-33 on the Sam Houston National Forest in Montgomery County, Texas, United States. CSE data collected on the site in Spring of 2020.

2.2 Workflow

The workflow is broken into major steps that consist of creating independent variables from lidar data, conducting an exploratory regression to filter independent variables, and using a small selection of them to model linear relationships with dependent variables or CSE data (Figure 2). The Upper Coast Lidar (UCL) dataset was used for my analysis and sourced from the Texas Natural Resources Information System website (Texas Natural Resource Information System, 2018). Lidar data was collected on January 13th, 2018 through March 22nd, 2018 during leaf-off conditions. UCL data was acquired using a manned aircraft at a nominal point density of 4.37 pts/m^2 (Texas Water Development Board, 2018).

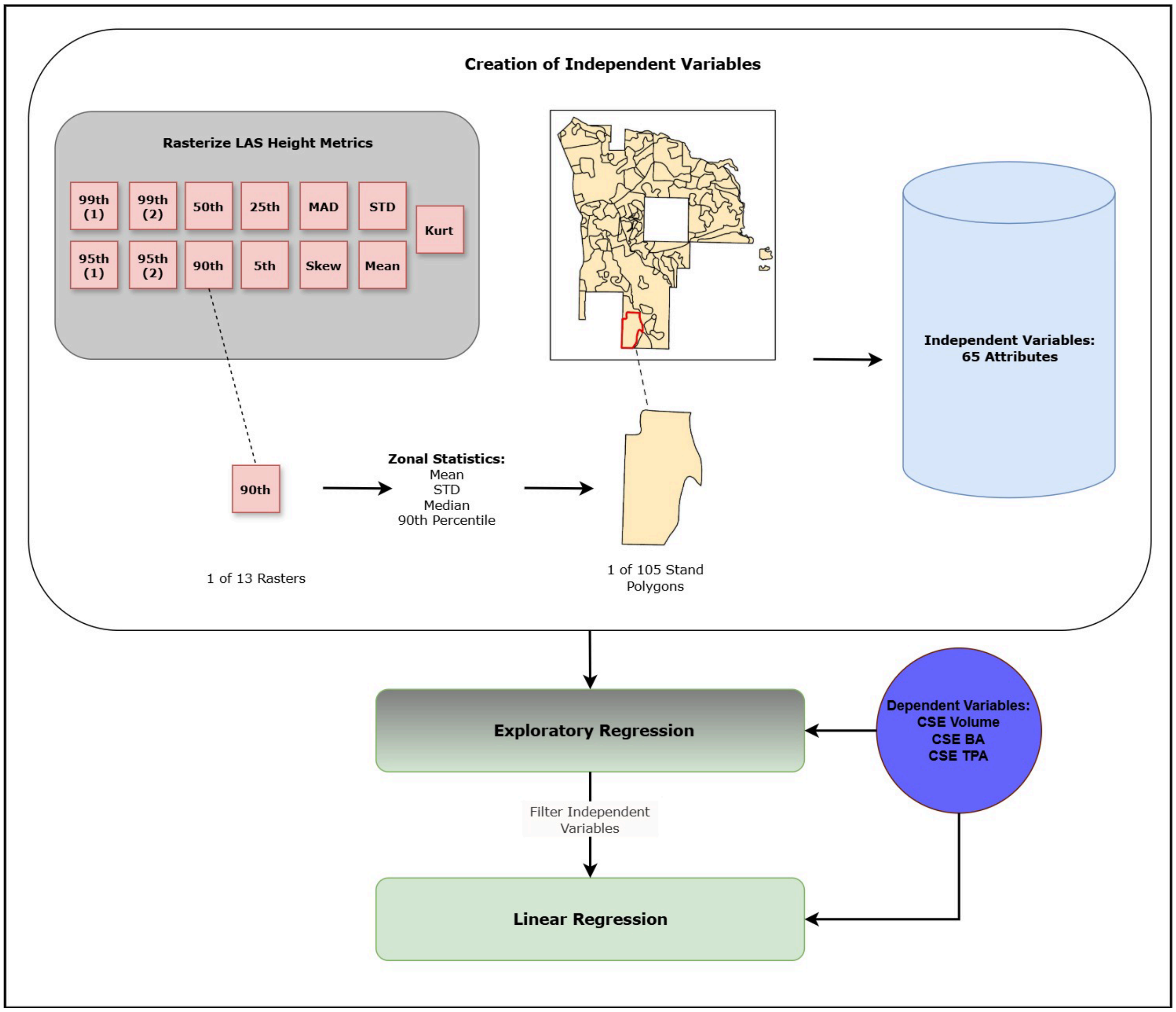

Fig. 2. A workflow of how lidar data was rasterized into height metrics, and zonal statistics were generated for each stand in the study area. The resulting independent variables were filtered using an exploratory regression, and a small selection of them were used to model linear relationships with CSE inventory data (dependent variables).

UCL point cloud data was imported into ArcGIS Pro software (ESRI, Redlands, California, U.S.), and rasterized into thirteen different height metrics at 1 x 1 m pixel resolution. Each height metric rendered a raster layer where output pixels are a calculated value of their spatially coincident lidar points. Height metrics included: 99^{th} and 95^{th} percentile height points at a 10 m height minimum; 99^{th} and 95^{th} percentile height points at a 1 m height minimum, 90^{th} percentile height points, 50^{th}

percentile height points, 25th percentile height points, 5th percentile heights points, median absolute distribution of height points, standard deviation (STD) of height points, kurtosis of height points, skewness of height points, and mean of height points.

After rasterizing these 13 layers, I calculated zonal statistics for each in all 105 stands. For example, the mean pixel value of 90th percentile heights were calculated within the area of each stand. Zonal statistics included mean, STD, median, and 90th percentile of pixel values, and a total of 65 attributes or independent variables were created. To filter out superfluous variables, I used exploratory regression in ArcGIS Pro to determine which variables had the most significant relationship with CSE metrics, the nature of their relationship (negative or positive), and eliminated redundant variables that violated issues of multicollinearity. This drastically reduced the number of variables that were later used when modeling linear relationships with CSE dependent variables.

2.3 Statistical Analysis

A tabular format of stand level CSE results, and their corresponding lidar-derived variables were exported from ArcGIS Pro and the remaining analysis performed in RStudio using R version 2024.04.2+764. Prior to performing any linear regression analysis, a Shapiro-Wilks test of normality and Breusch-Pagan test of homoscedasticity was generated for each dependent and independent variable pairing using the “rempsyc” package in R. Violations of either were noted later in results.

Using the most significant lidar-derived variable identified using exploratory regression, a linear regression was performed modeling relationships with the following dependent variables: CSE stand-level pine BA, pine TPA, hardwood BA, hardwood TPA, total BA, pine merchantable volume, pine board ft volume, merchantable volume of loblolly pine, board ft volume of loblolly pine, and merchantable volume of shortleaf pine. All my analysis was performed at a 95th confidence interval.

Results

3.1 Linear Regression: BA and TPA

Lidar-derived independent variables maintained a statistically significant relationship with stand-level CSE measurements of BA and TPA, but did not explain the variation well when modeling linear relationships ($R^2 < 0.4$). Both hardwood and pine groups had examples of independent variables that uniquely maintained significant relationships with BA and TPA, except for median MAD, which had a statistically significant relationship with both pine TPA and hardwood BA. Median zonal statistics were consistently the strongest independent variable for modeling linear relationships with BA and TPA metrics, including median skew, median MAD, and median kurtosis (Figure 3).

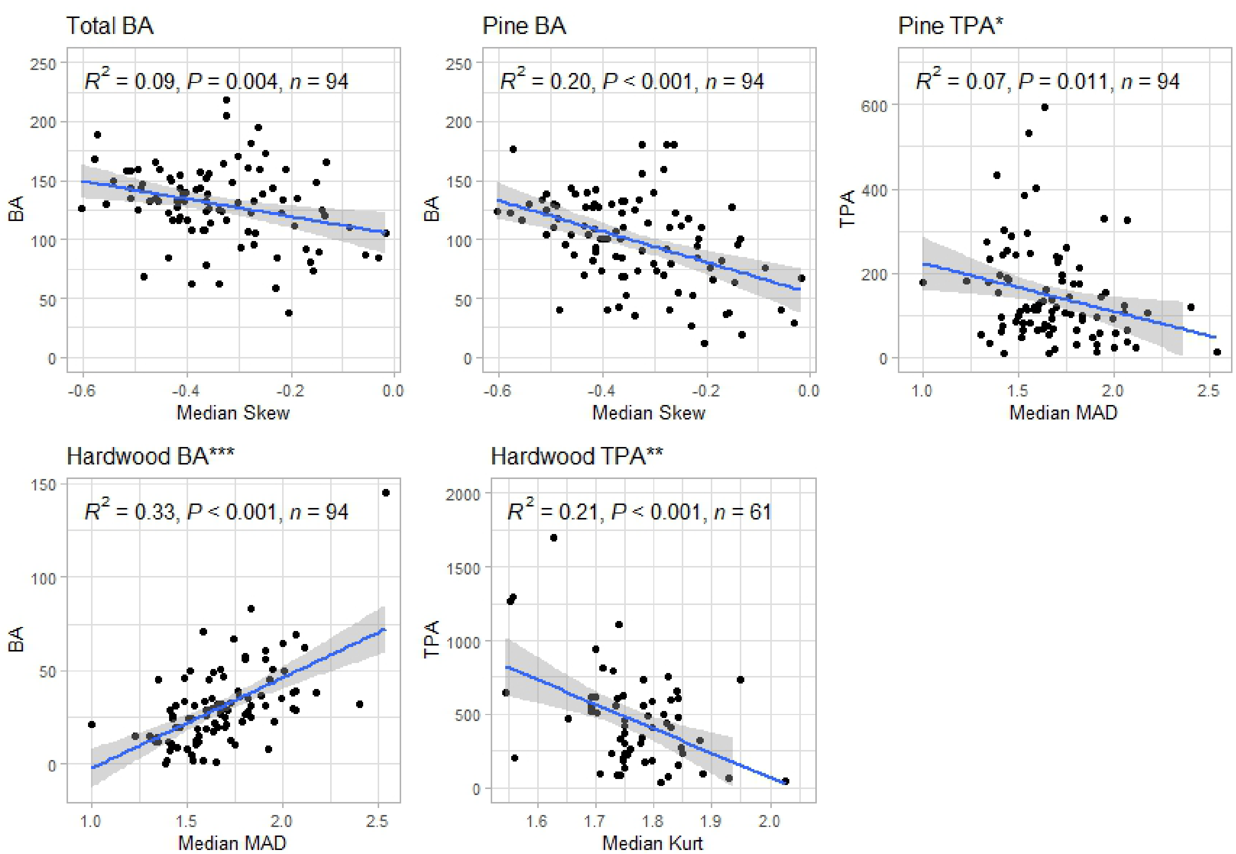

Fig. 3. Linear regression results for Total BA, Pine BA and TPA, and Hardwood BA and TPA. CSE data was used for dependent variables and lidar data was processed into independent variables. Violated assumptions of normality*, homoscedasticity**, and both*** are noted.

3.2 Linear Regression: Volume

Compared to linear modeling of BA and TPA, merchantable and board ft volume exhibited stronger relationships with certain lidar-derived independent variables. For all pine and loblolly pine volumes (merchantable and board ft), dependent variables demonstrated a statistically significant relationship with mean 95th percentile zonal statistics (Figure 4). These linear relationships explained relatively more of the variation in the dependent variable, with an R^2 of 0.5 or greater. STD 95th percentile zonal statistics was the strongest variable for modeling relationships with shortleaf pine volume during exploratory regression, but did not demonstrate a statistically significant relationship when performing linear regression (p = 0.063). It did however maintain a near statistically significant relationship, and notably, with an independent variable that was different from loblolly pine.

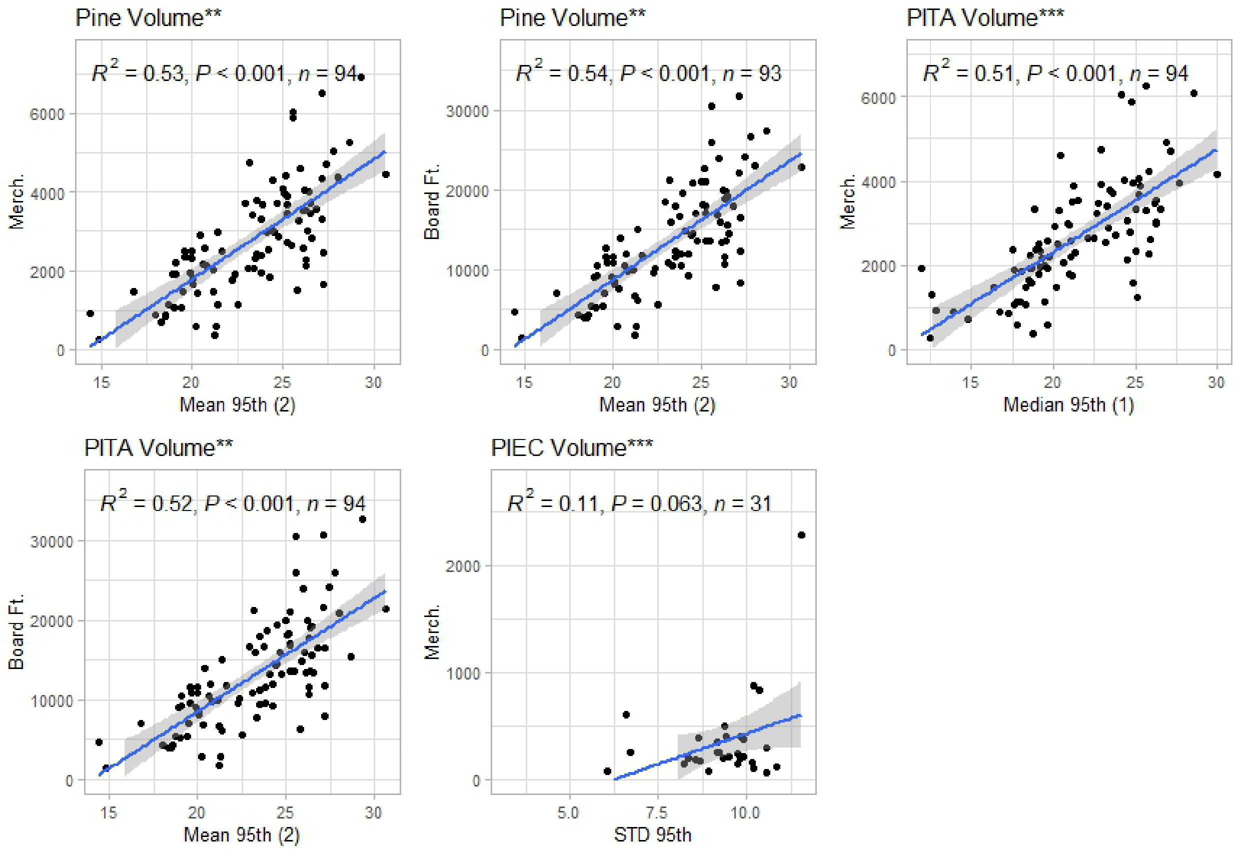

Fig. 4. Linear regression results for all pine merchantable and board ft. volume, loblolly pine (PITA) merchantable and board ft. volume, and shortleaf pine (PIEC) merchantable volume. CSE data was used for dependent variables and lidar data was processed into independent variables. Violated assumptions of normality*, homoscedasticity**, and both*** are noted.

Discussion & Conclusion

The results of my analysis indicate that open sourced lidar can be processed into explanatory variables that have the potential to model simple, linear relationships with traditionally collected CSE data. For BA and TPA CSE metrics, there were inherent weaknesses in my analysis, such as low explanation of variation, and violations of assumptions in linear regression. Despite statistically significant results when analyzing BA and TPA, this would make it unlikely that my current methods could be used to extrapolate reliable predictions of BA or TPA. More refined modeling techniques applied in similar scenarios, including data fusion (Popescu and Wynne, 2004; Lawrence, 2024) and deep learning (Mäyrä et al., 2021; Klauberg et al., 2023), might be potential avenues for improving the predictive capabilities of such models.

Linear relationships of lidar-derived variables and volume were stronger and showed potential to possess predictive capabilities. This indicates that these methods could successfully circumvent traditional field inventories where volume is an important consideration, although it is unlikely to be the only information necessary for informing management decisions. It was also of interest to determine whether shortleaf pine volume could specifically be modeled, because of its relatively low abundance compared to loblolly pine. Despite near significant results, we were unable to identify a lidar-derived variables that individually maintained a statistically significant relationship with shortleaf pine volume.

Similar studies have leveraged open-sourced Landsat and Sentinel 2 data to classify canopy coverage of southern yellow pine, including shortleaf pine and loblolly pine (Akumu and Amadi, 2022). In this example, canopy cover, and possibly stand-level species composition, might be determined. In other examples, hyperspectral data was used to investigate whether spectral characteristics specific to each southern yellow pine species could be distinguished using field-based (van Aardt, 2000) and remote sensing methods (Van Aardt and Wynn, 2007). Again, data fusion, and in particular non-visible light spectra generated from multispectral or hyperspectral sensors, are potential datasets that could increase the likelihood of successfully modeling shortleaf versus loblolly pine volume in future work.

Ultimately, this study demonstrates that open-sourced lidar data is a potential means for recreating CSE metrics, some of which maintain a strong enough relationship to make predictions of nearby and similar stand volume. This could translate to significant cost reductions and efficiencies, in the event traditional, personnel-intensive forest inventories could be augmented or replaced by remote sensing methods. Refinements of methodology, in particular fusing our lidar raster data with non-visible spectral data, could be one approach to modeling more accurate relationships with other CSE metrics like BA, TPA, and maybe even species-specific metrics.

Declarations

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material: Data can be made upon reasonable request to the corresponding author.

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Authors' contributions: BL: conceptualization, data curation, formal analysis, methodology, validation, writing - original draft, and writing - review and editing.

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