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

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Abstract

This study focuses on the development of a lidar-based methodology that recreates stand-level inventory results from Common Stand Exams (CSE). CSE protocols are the U.S. Forest Service's approach to measuring forest stocking and volume on public lands. Stand-level statistics of lidar-derived height metrics, individual tree height, and tree density were generated for 105 stands on the Sam Houston National Forest in Montgomery County, Texas, US. When comparing traditionally acquired CSE data versus lidar-based analysis, we successfully modelled linear relationship of stand-level pine basal area (BA) ($R^2 = 0.40$), trees per acre (TPA) of pine ($R^2 = 0.61$), and pine volume ($R^2 = 0.58$). Similar studies often compare lidar-based metrics to individual plot results, whereas our workflow demonstrated reasonable extraction of stand-level metrics from an established forestry protocol. While lidar-based approaches might not be appropriate for every forest management objective, our results demonstrate that they have the potential to be leveraged in scenarios where relatively coarse results are acceptable. 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, southern pine, forest inventory

Introduction

Stand-level forest inventory data is an important resource for managers 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-prohibitive 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 (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 are capable of modeling forest vegetation in precise detail (Sumnall et al., 2021; Ross et al., 2024). Examples include modeling tree height, canopy size, tree density, or even characteristics such as species richness and composition (Anderson et al., 2021; Wu et al., 2024).

Frequently, estimates of forest structure using lidar data are validated with plot-level field inventories (Means et al., 2000; Woods et al., 2008). It was our goal to quantify lidar inventory metrics at the stand level and compare them to results of an established inventory protocol called Common Stand Exams (CSE). CSEs are agency-specific forest inventory method used by the U.S. Forest Service. Also, we sought to do so with an open-source lidar dataset that would allow us to avoid the cost of acquiring project-specific data. For this study, a 2018 USGS airborne 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. We 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 CSE forest inventory.

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.

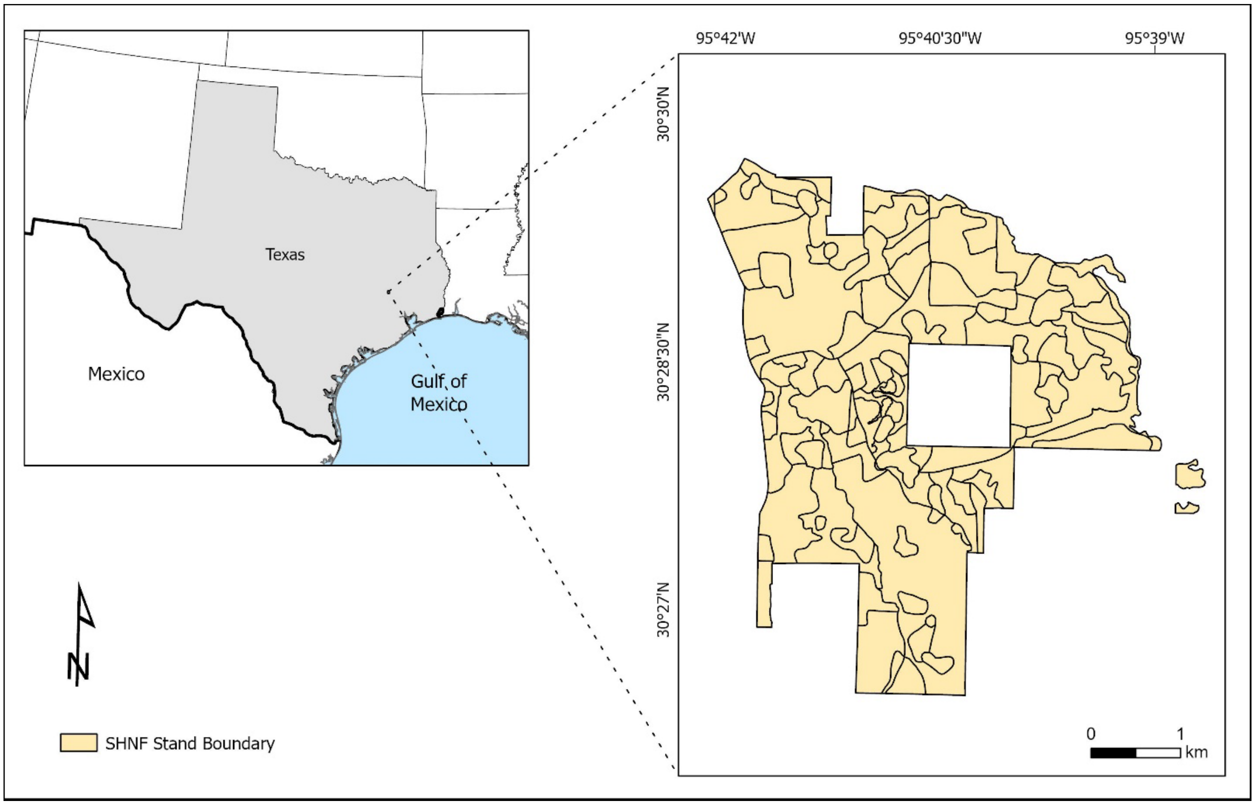

Fig. 1. Stands within Compartments 31-33 on the Sam Houston National Forest in Montgomery County, Texas, United States. CSE data collected on the site in Spring of 2020.

2.2 Workflow

The workflow is broken into three major steps that consisted of creating independent variables from lidar data, conducting an correlation analysis 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 our 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, with our study area using 11 of 9,758 tiles that comprise the entire UCL dataset. UCL data was acquired using a manned aircraft at a nominal point density of 4.37 pts/m^2 (Texas Water Development Board, 2018). Riegl LMS-Q680i and Riegl LMS-Q780 sensors were used at a flight altitude of approximately 780 m and a measurement range of 1 to 2 km. A significant portion of analyses in this study were conducted using the lidR package in R Studio (R version 2024.04.2+764) (Roussel et al., 2020) and ArcGIS Pro software (ESRI, Redlands, California, U.S.).

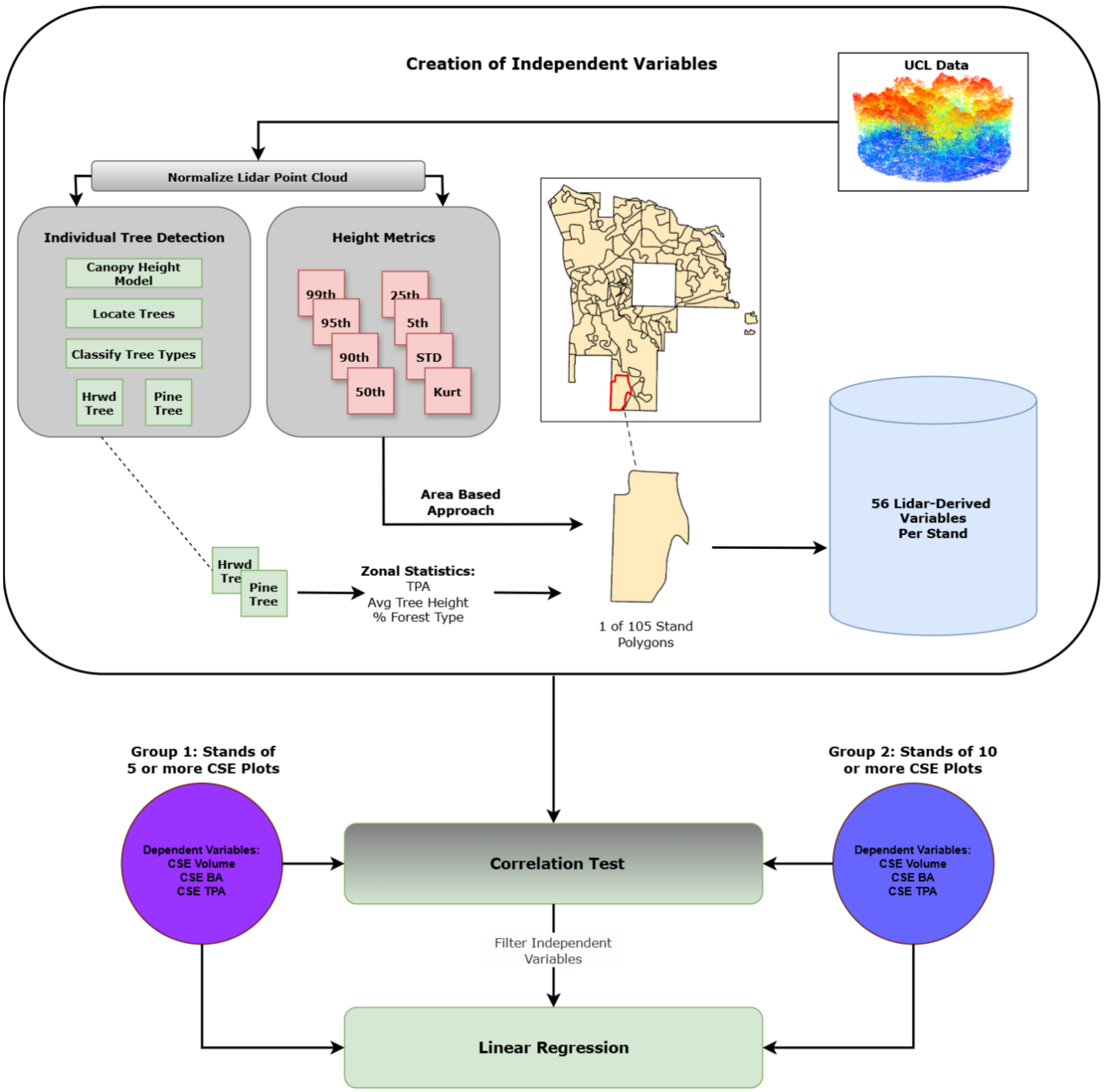

Fig. 2. A workflow of how lidar data was used to generate height metrics and individual tree detections. These were then used to generate zonal statistics for each stand in the study area. The resulting independent variables were filtered using a correlation analysis, and a small selection of them were used in a regression analysis with CSE inventory data (dependent variables).

2.2.1 Generating Lidar-derived Independent Variables

To support the evaluation of stand-level forest attributes, a total of 36 height metrics were generated for each stand (Table 1). Before generating height metrics, a catalog of tiled lidar files was created and normalized. An area-based approach was then used to generate metrics for regions of interest (ROIs) within the normalized point cloud. Our ROIs were created using a shapefile of 105 stands in the study area (Figure 2). Each stand was clipped from the point cloud, and lidar height metrics calculated for that respective stand.

Table 1. A summary of all lidar-derived independent variables (56 total) and CSE dependent variables used for analysis (12 total).

Variable Group	**Number of Variables**	**Variable Names**
Lidar-derived Independent Variables: 56 Total		
Height Metrics	36	zmax, zmean, zsd, zskew, zkurt, zentropy, pzabovezmean, pzabove2, zq5, zq10, zq15, zq20, zq25, zq30, zq35, zq40, zq45, zq50, zq55, zq60, zq65, zq70, zq75, zq80, zq85, zq90, zq95, zpcum1, zpcum2, zpcum3, zpcum4, zpcum5, zpcum6, zpcum7, zpcum8, zpcum9
Individual Tree Detection – All	8	all_mean_z, all_std_Z, all_max_Z, all_min_Z, tree_count, all_TPA, minority_forest_class_ercent, majority_forest_class_percent
Individual Tree Detection - Pine	6	pine_mean_z, pine_std_Z, pine_max_Z, pine_min_Z, pine_count, pine_TPA
Individual Tree Detection - Hardwood	6	hrwd_mean_z, hrwd_std_Z, hrwd_max_Z, hrwd_min_Z, hrwd_count, hrwd_TPA
Dependent Variables: 12 Total		
Stand-level CSE Metrics	9	total_BA, pine_BA, hrwd_BA, total_TPA, pine_TPA, hrwd_TPA, pine_cubic, pine_merch, pine_board

Besides the stand-level height metrics, individual tree detection was also performed within the study area. The cataloged and normalized lidar point cloud was first rasterized into a canopy height model (CHM). We used a pit free algorithm known for improving tree detection (Khosravipour et al., 2014), and post-processed the CHM using smoothing and filling. Trees were detected using a local maximum filter approach and a constant window size of 5 m. The resulting tree points and corresponding heights were exported to a shapefile format.

To identify which points belonged to major forest classes of pine or hardwood, we generated a classified raster of both forest types using supervised classification of imagery captured by the National Agricultural Imagery Program (NAIP) (USDA, n.d.). NAIP imagery was made up of 60 cm resolution RGB and near-infrared bands and was collected the same year as our UCL lidar dataset (December 2018). A simple class schema of "pine", "hardwood", and "other" was used to classify pixels. Once a classification raster was created, each tree detection point was assigned a forest class based on the pixel type it spatially coincided with. Zonal statistics were then calculated that considered the total number of trees, TPA, average tree height, maximum tree height, and minimum tree height per stand. These metrics were individually generated for all trees, pine trees, and hardwood trees. A total of 20 individual tree detection metrics were generated and used as lidar-derived independent variables (Table 1).

2.2.1 Statistical Groups and Analysis

CSE inventory data was collected from March 2020 to June 2020 using protocols detailed in the U.S. Forest Service's Region 8 Common Stand Exam Field Guide (Region 8 – Common Stand Exam, n.d.). Despite an approximately 2-year difference in lidar data capture and the CSE field inventory, there was little to no change to forest structure quantified in our analysis. This included large, mature pine trees that are the focus when managing southern forests in our region. CSE stand level metrics, or dependent variables, included: total BA, pine BA, hardwood BA, pine TPA, hardwood TPA, board ft volume of pine, merchantable volume of pine, and cubic volume of pine. Stands were divided into two statistical groups: the first included stands where 5 or more CSE plots were collected, and the second where 10 or more CSE plots were collected. This allowed the analysis to focus on stands where sufficient field data was gathered. Prior to performing any linear regression analysis, a Pearson's correlation was calculated to assess relationships between all variables and filter out non-significant ones. The "metan" package in R was used to expedite this process, and narrow down examples of statistically significant relationships between independent and dependent variables, and the strength of their correlation. For both statistical groups, linear regression was performed at a 95th confidence interval using dependent and independent variables with the strongest correlation. Using the "rempsyc" package in R, we tested all models for assumptions of normality, heteroscedasticity, and autocorrelation of residuals. Any models violating the assumptions necessary for linear modeling were excluded from our results.

Results and Discussion

3.1 Linear Regression: 1st Group

When analyzing CSE stands that were comprised of 5 plots or more (n = 43), we identified numerous examples of lidar-derived variables and CSE metrics with statistically significant relationships. Amongst these, a smaller number met the assumptions of linear regression, of which we have shared the best performing models (Figure 3). Total BA and pine BA were both significantly predicted (P < 0.001) by estimates of pine TPA created from individual tree detection ("lrd_pine_TPA"), with models explaining 31% and 41% of the variance, respectively. The lidar-derived height metric "zq55" significantly predicted (P < 0.001) hardwood BA and explained 22% of the variance. Pine board volume, pine cubic volume, and pine merchantable volume were all significantly predicted (P < 0.001) by both individual tree and height metrics, with 32-41% of the variance explained. When analyzing this group, we did not successfully model pine or hardwood TPA with any lidar-derived variables.

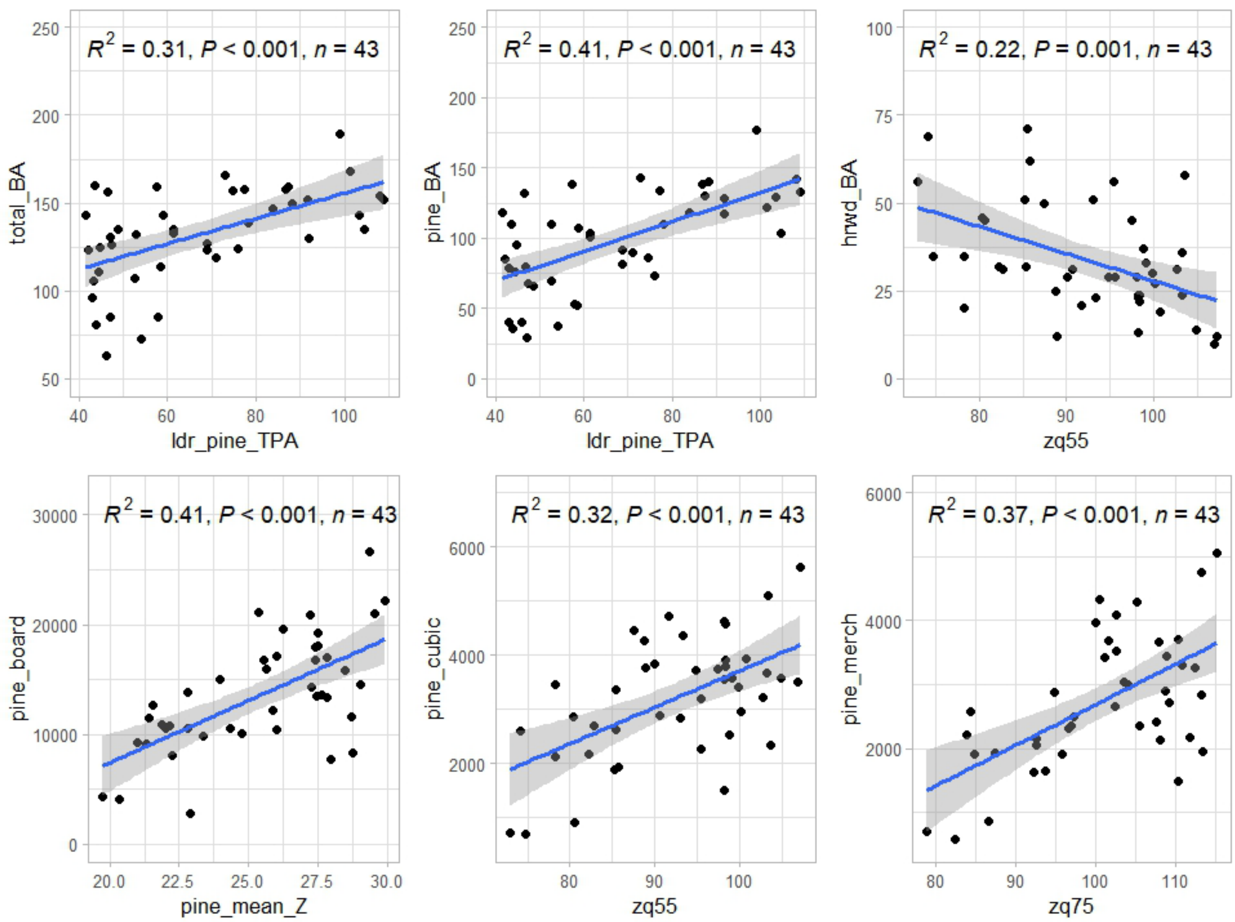

Fig. 3. Results of linear regression when modeling CSE metrics and lidar-derived variables in stands where 5 or more CSE plots were collected.

3.2 Linear Regression: 2nd Group

For CSE stands with 10 or more plots (n = 16), lidar metrics generated from individual tree detection consistently produced the highest performing models, with one exception. Both total BA (P = 0.008) and pine BA (P = 0.009) were significantly predicted by lidar measurements of all TPA (“ldr_all_TPA”), with linear regression explaining 41% and 40% of the variance, respectively. Lidar measurements of average tree height per stand (“all_mean_Z”) significantly predicted pine TPA (P <

0.001) and pine board ft. volume (*P* < 0.001). For those models, lines of best fit explained 61% of the variance for pine TPA and 58% for board ft. volume. Volume of merchantable pine was significantly predicted (*P* = 0.002) by the lidar height metric "zq75", with 51% of the variance explained.

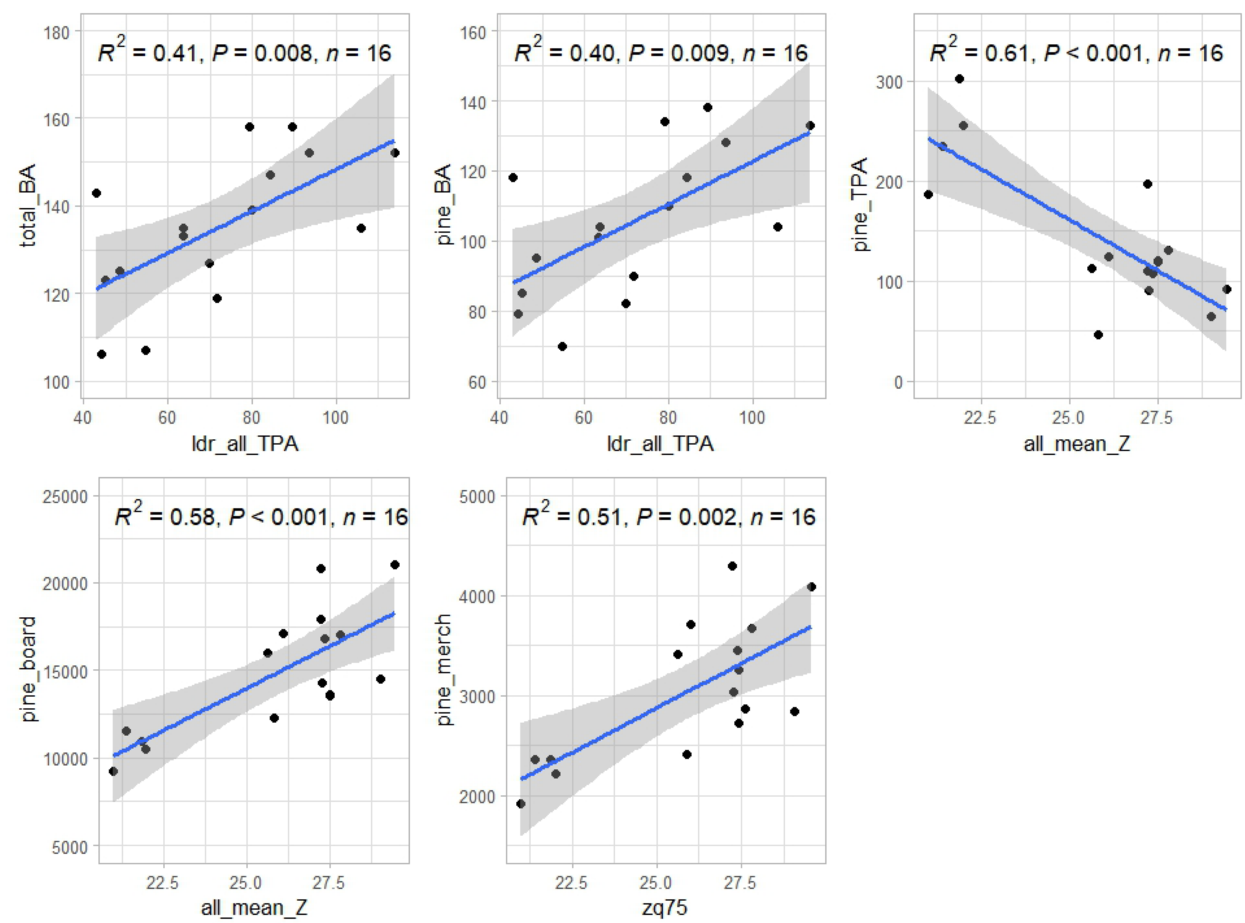

Fig. 4. Results of linear regression when modeling CSE metrics and lidar-derived variables in stands where 5 or more CSE plots were collected.

3.3 Lidar and Stand-level Inventories

The results of our analysis indicate that open sourced lidar can be processed into explanatory variables used for modelling predictions of traditionally collected CSE data. This was true of lidar-derived metrics from individual tree detection and height metrics, with both being statistically significant predictors of a variety of CSE dependent variables. Amongst our 9 dependent variables, we were able to successfully create predictive linear models for all but hardwood TPA and TPA for all forest types. Of the numerous studies published exploring the use of lidar to generate forest attributes, we only identified one that focused on the U.S. Forest Service's CSE protocol (Hummel et al., 2011). In their study, they had limited success modeling CSE stand volume, whereas our analysis successfully modelled volume in CSE stands of 5 or more plots, and 10 or more plots.

Whether our methods could be practically applied in a real-world setting is arguably circumstantial. For example, we excluded stands comprised of very small amounts of plots from our analysis (<5 plots). Additionally, several of our models explained a small amount of the variance (<50%) and therefore have arguably limited predictive capabilities. In some scenarios, however, it is plausible that our methods could be used for generating coarse estimates of forest structure at the stand level. Based on our results for CSE stands of 10 plots or more, modeling predictions of pine structure could be reasonably achievable. As the U.S. Forest Service is confronted with directives to increase timber production, our proposed methods could be one approach to generating estimates of stand-level structure in similar southern pine stands (USDA, 2025).

Efforts were made to improve our results by analyzing our data with machine learning models, such as random forest and best subset regression. We consistently encountered comparable, or even reduced model performance. We speculate this could be attributable to multicollinearity amongst several of our predictor variables. This was especially true of our lidar height metrics. In future work, we would consider expanded methods, like data fusion (Popescu and Wynne, 2004; Lawrence, 2024) and deep learning modelling (Mäyrä et al., 2021; Klauberg et al., 2023) to improve our analysis. Data fusion of lidar with non-visible spectra, like in Landsat or Sentinel satellite missions, is one avenue for potentially increasing the predictive powers of our analysis. Non-visible spectra have been applied previously to classify canopy coverage of southern yellow pine (Akumu and Amadi, 2022). 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).

Conclusion

The U.S. Forest Service owns 193 million acres of public land, and despite having an agency-specific forest inventory method, there are limited examples of lidar-derived inventories being applied to the CSE protocol. Our 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 structure and 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.

Declarations

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Competing interests: The authors declare that they have no competing interests.

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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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