

Original Articles

Mapping percent canopy cover using individual tree- and area-based procedures that are based on airborne LiDAR data: Case study from an oak-hickory-pine forest in the USA

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ABSTRACT

Canopy cover (CC) is the proportion of a forest floor covered by the vertical projection of tree crowns. Recently, it has become common to utilize LiDAR (light detection and ranging) canopy metrics to estimate CC over large areas. However, these metrics are primarily related to canopy density rather than the specific definition of CC. Here, two processes that employed individual tree segmentation (ITS) and area-based procedures based on LiDAR data are presented to estimate CC across the Talladega Division of the Talladega National Forest (93,694 ha) at the plot, stand, and landscape levels. The two analytical procedures were assessed using the results of a plot/grid method as a reference dataset, which focused on CC estimates within 255 field measurement fixed-area sample plots. The accuracy of a third process, employing an imagery-based visual CC assessment, was also compared against the two procedures and the reference dataset. The LiDAR-based analytical procedures were able to provide estimates of CC with an RMSE of approximately 15 %, which is acceptable for landscape-level assessments. Based on the results of this study, we conclude that CC maps, when created using LiDAR data, may be suitable for various operational tasks such as assessing the impact of forest disturbances and helping to determine the habitat suitability for certain wildlife species.

1. Introduction

1.1. The importance of canopy cover estimates in forestry

Canopy cover (i.e., crown closure, here after CC) is defined as the percent of ground covered within a given area by individual tree crowns, based on a vertical projection of the edge of each tree's crown down to a horizontal plane (van Laar and Akça, 2007). At a local scale, a CC value of 100% refers to a fully tree-covered area while a CC value of 0% refers to a canopy gap, forest opening, or basic open area, where sunlight resources are available to plants (perhaps other than trees) that may grow nearer to the ground surface. The “given area” is of course an important aspect here, as large forested landscapes would contain a mosaic of open and closed areas, and the average CC across the landscape may be presented as a single value.

Canopy cover is a key biophysical measure widely used in the forestry field because many ecological processes and forest functions, such as plant survival, hydrological cycle, snow accumulation, wildlife habitat, and competition between overstory and understory plants can be related to the availability of sunlight reaching the ground surface (Jennings et al., 1999; Ko et al., 2009; Stojanova et al., 2010; Akturk et al., 2023). For example, local scale understory plant composition and density can be associated with canopy gaps or small openings within a forest (Franklin et al., 2018). A dense plant understory with shade-intolerant vegetation might be observed in forest gaps where the CC is virtually 0%. In these cases, sunlight directly reaches the forest floor, which can promote the growth of grasses, shrubs, and shade-intolerant trees. From an ecological perspective, the presence of understory plant species may be desirable to provide food resources for certain wildlife species as well as maintain biologically diverse habitats (Franklin et al.,

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2018). However, the presence or composition of understory plant species may also be undesirable by forest managers due to increased competition for resources with desired overstory tree species (Nowacki and Abrams, 2008). Therefore, forest managers might prescribe treatments that change CC levels to help address forest management objectives.

Forest cover maps might be informed by an estimate of CC, as it might serve as a stratification criterion for classification processes (Ko et al., 2009; Turkish General Directorate of Forestry, 2017; Food and Agriculture Organization of the United Nations (FAO) 2020). At a minimum, according to the FAO, a forest must have more than 10% CC to qualify as “forest”. Further, in many other countries the CC is used to distinguish not only forest conditions, but conditions of woodlands and savannas (Ko et al., 2009). In Turkey, CC is one of the three criteria, along with dominant tree species and stand developmental stage, which are used to delineate forest stand boundaries and inform the stand types. A stand type in this system is considered loosely covered (11–40% CC), moderately covered (41–70% CC), or fully covered (71–100% CC). Stand types with a CC of less than 11% are considered degraded (Turkish General Directorate of Forestry, 2017). Differences in forest definitions can lead to disagreements between a country’s estimate of total forest area and that which is reported by the FAO. In the U.S., one nation-wide CC map was developed using approximately 63,000 reference forest plots that were used to train a machine learning model to predict tree canopy cover, resulting in a 30-meter spatial resolution raster dataset that complemented other land use change estimates (Ruefenacht et al., 2022).

Forest inventories are another example of the widespread use of CC estimates, since CC is often correlated with other important forest characteristics. In some cases one can observe a positive correlation between CC and tree density as well as stand volume (van Laar and Akça, 2007). Strong positive correlations between the CC, tree diameter at breast height (dbh), aboveground biomass, and carbon stocks have also been reported (van Laar and Akça, 2007; Yücesan et al., 2019; Henn and Peduzzi, 2023). Since a CC estimate is a powerful attribute that may indicate the degree to which a landscape is occupied by trees, it can provide information for decisionmakers and inform silvicultural treatments, as resource managers can manipulate a forest canopy to create an environment where desirable plant species can grow (Jennings et al., 1999; Franklin et al., 2018). Therefore, forestry professionals, silviculturists, and researchers seek practical methods to estimate CC in a cost-effective manner that provides a reasonable level of accuracy.

1.2. Methods used for canopy cover estimation

There exists a rich variety of field-based methods for CC estimation (Fiala et al., 2006; Ko et al., 2009), which involve simple ocular estimates (Jennings et al., 1999; Turkish General Directorate of Forestry, 2017), measurements of tree crown dimensions (Tausch et al., 1981), estimates from line intersect methods (Canfield, 1941), the use of a moosehorn (Robinson, 1947) or densitometer (Stumpf, 1993), and outcomes of analyses that use remotely sensed imagery (Hu et al., 2007). Although some of these methods have been widely used for decades, there is no standard, at times resulting in moderate variability among CC estimates for the same study area (Fiala et al., 2006; Ko et al., 2009). More importantly, field-based methods can be limited in the extent of coverage across a landscape. Research has pointed out the difficulties of traditional, field-based measurements due to their time-consuming and labor-intensive nature (Stojanova et al., 2010; Gao et al., 2022; Akturk et al., 2023). Given the limitations of field-based methods, analyses involving remotely sensed imagery are often employed today for acquiring estimates of CC (Gao et al., 2022; Ruefenacht et al., 2022) and other forest attributes (Coops et al., 2021). Some have highlighted a growing interest in using remote sensing to estimate CC, where analytical tools are constantly diversifying and where the quality of estimates is constantly increasing (Ko et al., 2009; Coops et al., 2021).

Interestingly, the use of remote sensing for CC estimates is not new to the forestry field. The interpretation of aerial photographs to obtain detailed CC estimates dates back to the 1940s (e.g., Standish, 1945; Moessner, 1947; Spurr, 1948). After some training and experience, CC can be ocularly assessed at a fine scale on single aerial photographs. van Laar and Akça (2007) state that photogrammetric methods such as these may be more accurate, less time consuming, and less subjective than other field-based methods for CC estimations.

Recently, the spatial, spectral, and radiometric resolution of satellite-based imagery has improved dramatically, making these products more valuable for estimating CC than traditional aerial images. In addition, the area covered by a single satellite-based image results in greater cost-efficiency. Thus, satellite-based optical data might be viewed as more effective today than aerial imagery for estimating CC over broader landscapes (Huang et al., 2001; Ruefenacht et al., 2022). Depending on the spatial resolution of the pixels contained within satellite images, CC analyses might be performed at different scales, from single tree (Weisberg et al., 2007), to plot (Kahriman et al., 2014), or broader scales (Chen et al., 2002). As one might expect, the most precise estimates of CC might be achieved through single-tree level analyses, but it is impractical to physically analyze each tree crown across a vast forest landscape. This is why tree-level analytical procedures are usually automated using pixel- or object-based image analysis (OBIA) approaches.

OBIA approaches are often preferable to pixel-based approaches today because they typically yield more consistent outputs in forest cover mapping (Blaschke et al., 2008; Yurtseven et al., 2019). One problem with OBIA approaches is the lack of a standard for parameterization of the process; thus, resultant CC maps may be highly subjective depending on an analyst’s skill and knowledge (Kim et al., 2008; Yurtseven et al., 2019). When employing coarser analyses, statistical- or physically based predictive models are commonly developed (Gao et al., 2022). These models are informed by field data measured within sample plots, and subsequently the data are estimated over broader regions. However, Fiala et al. (2006) noted that the outcomes from predictive models may be less accurate than outcomes from field-based CC estimation methods. Such modeling approaches are also limited to areas where sample data are collected, which results in low applicability across broader areas (Gao et al., 2022). Furthermore, an inappropriate distribution of sample plots to forests with varying CC may lead to biased outcomes of models and maps. Because of such limitations, the use of light detection and ranging (LiDAR) for estimating forest CC is of interest among researchers in recent years as an alternative source of data (Vatandaslar and Zeybek, 2021; Atkins et al., 2023; Akturk et al., 2023; Henn and Peduzzi, 2023).

With careful development of mathematical algorithms, forest structure information can be estimated using LiDAR point clouds, permitting the development of maps of forest condition for different periods of time at different scales (Wulder et al., 2012; Coops et al., 2021). As an example, using low-density airborne LiDAR (sometimes called airborne laser scanning—ALS) data collected in 2009 and 2013, Arumäe et al. (2020) analyzed the change in CC before and after thinning operations in a hemi-boreal forest located in northern Estonia and illustrated the slight decrease in CC among thinned stands. More recently, Henn and Peduzzi (2023) used airborne LiDAR data and aerial imagery to estimate CC of urban forests throughout Athens-Clark County, Georgia (USA). And Pu et al. (2023) compared different individual tree segmentation (ITS) methods to obtain the most accurate characterization of tree crowns from drone-based LiDAR data. In this case, lower elevation drone flights, when compared to aircraft flown at higher elevations to obtain aerial imagery, provided denser point clouds and resulted in better representation of individual trees over relatively small areas. Finally, in a study from western Slovenia, Stojanova et al. (2010) used airborne LiDAR, satellite imagery, and machine learning techniques to estimate CC, with one predictive model having an R^2 value of 0.77 and a RMSE of 14%.

Assessing CC is common among wildlife and conservation planning communities, as it is suggested that certain wildlife species prefer certain ranges of CC within a forest (Fiala et al., 2006; McNeil et al., 2023). Researchers are increasingly using LiDAR-based CC estimates to help understand habitat preferences of forest-dependent wildlife species or to develop more reliable wildlife species distribution models. For example, Smart et al. (2012) developed models for the red-cockaded woodpecker (RCW) (*Leuconotopicus borealis*) using the MaxEnt species distribution algorithm and observed an 8% improvement in model performance when combining airborne LiDAR with classic environmental variables. CC was the greatest contributor to the distribution model of RCW among all other LiDAR metrics. In another study,

Garabedian et al. (2014) used LiDAR data to help define habitat thresholds for RCWs, and noted that an appropriate foraging site should have a hardwood CC of less than about 6% in a mixed pine forest setting. McNeil et al. (2023) focused on another forest-dependent species, the golden-winged warbler (*Vermivora chrysoptera*) and using LiDAR metrics suggested that bird occupancy probability was negatively correlated with litter cover and positively correlated with herbaceous cover attributes.

Most studies utilizing LiDAR to estimate CC rely on canopy metrics (i.e., proxy indicators) that are typically based on the ratio of laser returns above a specified height threshold. These metrics are related to canopy density rather than the specific definition of CC, which is “the proportion

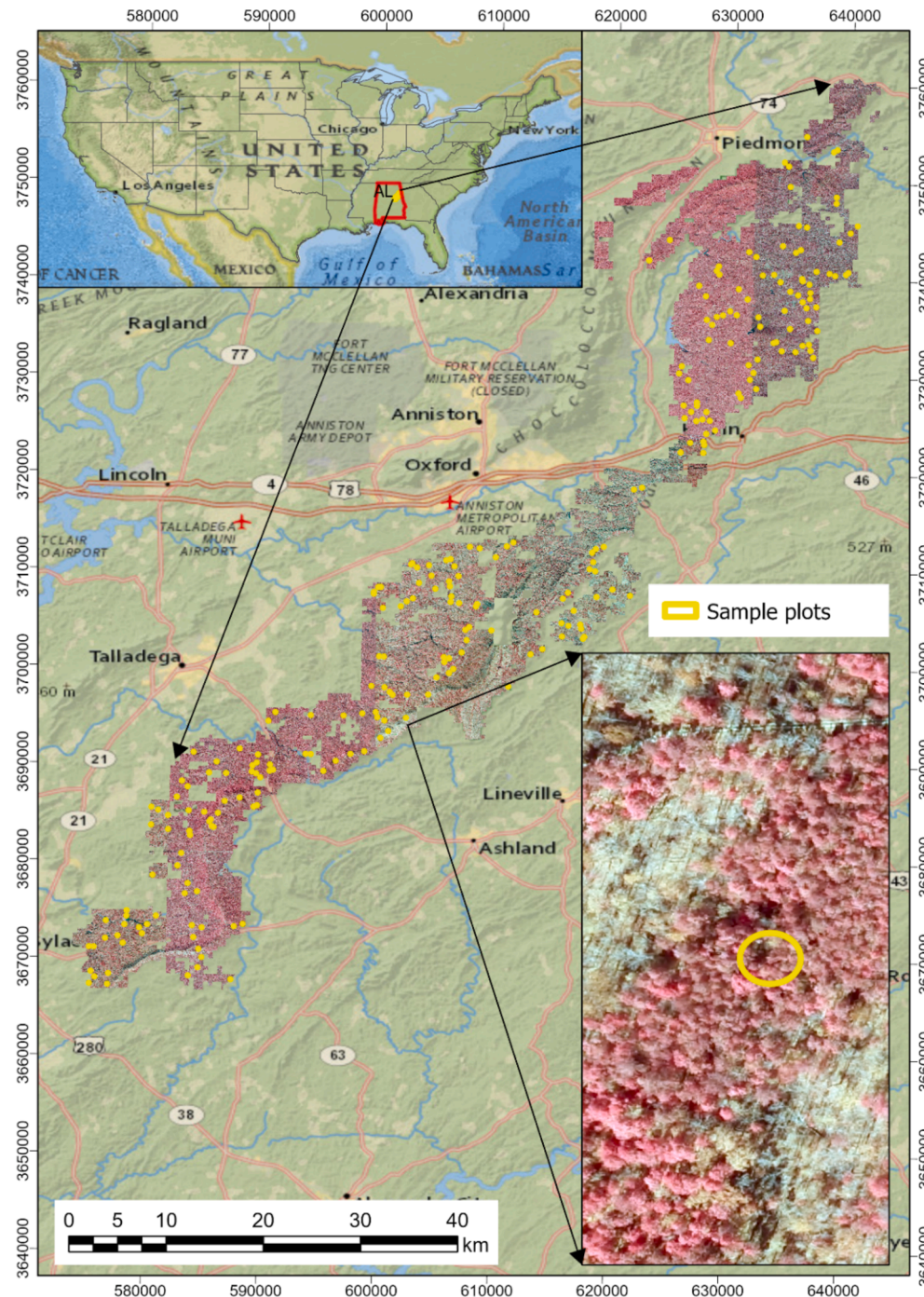


Fig. 1. Talladega National Forest in northeastern Alabama (USA) and the location of field measurement plots (near-infrared image courtesy of the U.S. Department of Agriculture NAIP imagery program. Basemap source: Esri).

of the forest floor covered by the vertical projection of the tree crowns" (Jennings et al., 1999). To meet the criteria of this definition, direct ITS algorithms, such as *silva2016* (Silva et al., 2016), *PTrees* (Véga et al., 2014), *Li2012* (Li et al., 2012), and *dalponte2016* (Dalponte and Coomes, 2016), might be employed for crown delineation purposes. At times, the outcomes from using these algorithms need to be converted to an interval of 0–100% CC to be useful for operational forest inventories or management planning. To the best of our knowledge, some studies have used direct ITS algorithms to estimate CC (Gao et al., 2022; Henn and Peduzzi, 2023; Pu et al., 2023), however, none of these efforts have reported the creation of a continuous CC map, likely due to the vector-based nature of the algorithms.

Therefore, the main goal of the present study was to develop a framework for creating a relatively accurate CC map for a large forest area relying solely on airborne LiDAR data. Our specific objectives include: (i) to develop analytical procedures for creating CC maps based on LiDAR data, and (ii) to compare the outcomes with a reliable reference dataset that is based on an established method that uses U.S. Department of Agriculture National Agriculture Imagery Program (NAIP) aerial imagery.

2. Materials and methods

2.1. Study area and field plots

The research is centered on the Talladega and Shoal Creek Ranger Districts (the Talladega Division) of the Talladega National Forest, located in the northeastern region of the State of Alabama, USA (Fig. 1). The study area is 93,694 ha in size, consisting of forests, roads, ponds, fields, and gas and electrical rights-of-way. The elevation varies from 152 m to 734 m above sea level, encompassing both the Ridge and Valley and the Piedmont ecoregions. The climate in this area is subtropical, summers are hot and humid, while winters are relatively mild, and on average the annual precipitation amount is approximately 1260 mm. In general, the forests are characterized by oak-hickory-pine communities that grow on shallow, excessively drained soils (Carter and Cobb, 2012). Pine forests contain longleaf (*Pinus palustris*), shortleaf (*P. echinata*), loblolly (*P. taeda*), and Virginia pine (*P. virginiana*) species, particularly on top of ridges and on south-facing slopes (Womack and Carter, 2011). Deciduous forests contain oaks (*Quercus* spp.), blackgum (*Nyssa sylvatica*), red maple (*Acer rubrum*), sourwood (*Oxydendrum arboreum*), sweetgum (*Liquidambar styraciflua*), tulip poplar (*Liriodendron tulipifera*), hickory (*Carya* spp.) and other species (Carter and Cobb, 2012). There are a number of mixed coniferous / deciduous forests as well where natural forest regeneration processes were employed. Fire plays an important role in managing community composition, and prescribed fire is a significant management tool that the managers of the study area use to help achieve desired ecological conditions. The current fire return interval, from both wildfires and prescribed burns, is estimated to be approximately 6 years across more than half of the forested area (Stober et al., 2020), although the natural historical return interval for pine-dominated upland sites is about 3 years according to dendrochronological analyses (Bale, 2009).

In early 2022, 255 field measurement plots were measured by a U.S. Forest Service field measurement crew. Each circular plot had horizontal radius of 11.4 m (37.2 feet) and covered an area of 404.6 m² (i.e., 0.1 acre). These plots were randomly distributed using a k-means clustering algorithm across the study area (Fig. 1) in a manner that represented a wide range of forest structures, such as pure, mixed, coniferous, deciduous, fully and sparsely covered, and newly regenerated stands. The field measurement crew located the plot centers using a mapping-grade GNSS receiver (Trimble R1). While several biophysical characteristics of all tree species (> 7.6 cm) within the plots were measured, no data related to tree crowns or canopy cover were measured or estimated during field surveys.

2.2. Remotely sensed data

Airborne LiDAR data was collected between December 2020 and February 2021 using a Leica Terrain Mapper. This mission covered the entire study area and had an average point spacing of 0.32 m (5.1 pts/m²). From a spatial assessment of 441 survey locations across the State of Alabama, the horizontal and vertical accuracy of this set of data were 0.71 m and 0.051 m, respectively. Therefore, the data meets the positional accuracy standards for digital geospatial data of the American Society for Photogrammetry and Remote Sensing (2023). The LiDAR data was used within two analytical procedures that are described below.

Color infrared, county-level mosaics were provided by the U.S. Department of Agriculture NAIP program. The mosaics for five Alabama counties were downloaded from U.S. Department of Agriculture's Geospatial Data Gateway (datagateway.nrcs.usda.gov). The NAIP imagery was acquired in the late fall of 2021, and had a spatial resolution of 0.3 m. The NAIP imagery contained four spectral bands: red, green, blue, and near-infrared; thus, it was possible to separate actual tree crowns from other vegetation (e.g., grass, understory) through distinct reflectance patterns in the true color and near-infrared bands. This data served as a base map for an accuracy assessment of LiDAR-based CC maps, as it allowed a reference CC to be developed using an established image interpretation process.

2.3. LiDAR data processing

The LiDAR dataset contained 635 LiDAR (.LAS) files. These files were processed using Rstudio (R version 2023.06.1 Build 524) within the high-performance computing system (Sapelo2) of University of Georgia. Due to the size of raw .LAS data files, parallel computing was employed, so a total 21 of the cores with 900 GB RAM were utilized in processing the LiDAR point clouds. From the raw LiDAR point clouds covering the study area, returns only from the ground (the last returns) were selected to develop a digital terrain model (DTM) representing the elevation of study area. The DTM was created with 1 m spatial resolution using the triangular irregular network (TIN) method. The decision regarding spatial resolution was made with consideration of point spacing and the point counts within each tile. A canopy height model (CHM) was created by subtracting the DTM from the LiDAR point cloud first returns (i.e., the digital surface model or DSM). Then, the CHM was filtered removing any negative values and values higher than 95% of tree height to reduce noise. The denoised point clouds were used as input data for the workflows described in the next subsection.

2.4. Spatial analysis and mapping

Two analytical procedures based on the LiDAR data were employed to create continuous maps illustrating the CC estimates (%). The first was an individual tree-based procedure, relying on Voronoi polygons to extract crown boundaries. To this end, we applied the *silva2016* algorithm (Silva et al., 2016) in the Rstudio *LidR* package (Roussel et al., 2020) given performance demonstrated in other studies (Henn and Peduzzi, 2023; Pu et al., 2023) and its availability. The algorithm basically used a local maximum filtering to detect treetops from CHM within a certain size of moving window. Based on the detected treetops, a variable radius crown buffer was applied to delineate the initial tree crown area. Then, the centroidal Voronoi tessellation approach was used to segment the individual tree polygon. Pixels above 30% of treetop heights were isolated as individual tree crown to remove the low-lying noise (Silva et al., 2016).

The second was an area-based procedure widely used in airborne LiDAR-based forest inventories (Bouvier et al., 2015; White et al., 2017). This procedure utilized a reclassified CHM to filter pixels >3 m in height (i.e., trees) and calculate CC as the proportion of canopy pixels relative to the area of the plot, stand or grid cells. A third process involving

expert knowledge through aerial image interpretation was also employed as a contrasting method.

2.4.1. Procedure #1 (Individual tree-based)

The *silva2016* algorithm (Silva et al., 2016) was applied to the denoised point clouds for individual tree segmentation and shapefiles were created that contained vector polygons (one polygon per tree) representing individual tree crowns (Fig. 2). This dataset was georeferenced to a projected coordinate system (NAD 1983 (2011) UTM Zone 16N) in ArcGIS Pro 3.0 to enable calculation of each crown area (m²). The tree crown GIS layer was then intersected with vector layers that represented the field measurement plots, forest stands delineated for the study area, and a 30-m square vector grid created for the entire study area using ArcGIS Pro's *Fishnet* function. The reason for choosing a moderate spatial resolution was based on pragmatic considerations and the findings from Atkins et al. (2023), which indicated that CC could be estimated with a high degree of certainty when spatial grain was adjusted to a size between 25 and 75 m.

The results of these intersect processes were three different vector GIS layers: the total crown area of trees within each field measurement plot, forest stands delineated for the study area, and 30 m grid cells. Subsequently, a new field (attribute) was added to the GIS layers so that CC could be estimated using the size of each field measurement plot (404.6 m²), forest stand (variable), and 30 m grid cell (900 m²):

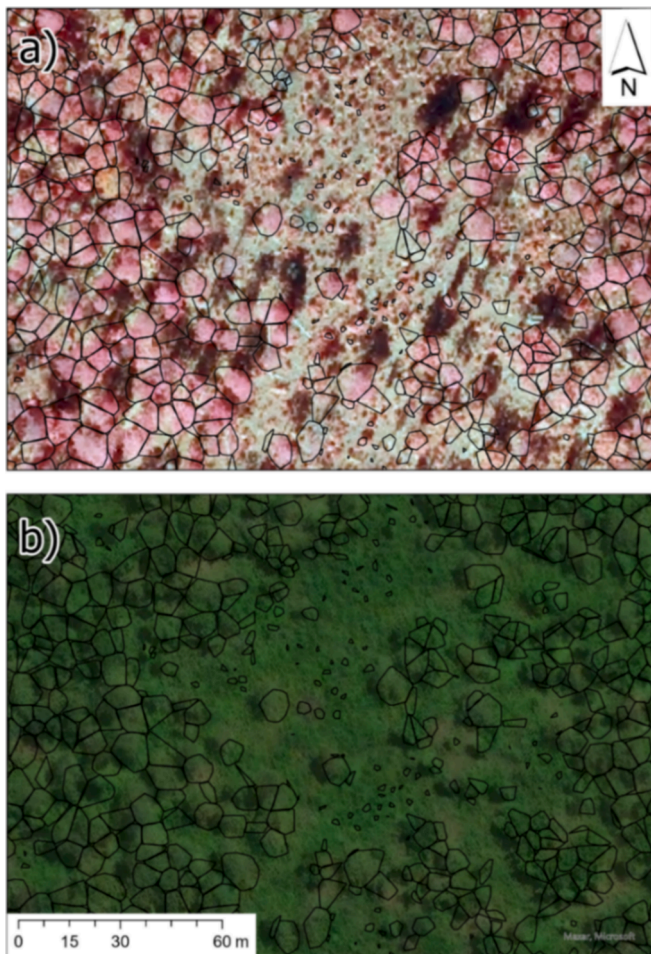


Fig. 2. Individual tree segmentation results overlaid on a) a near-infrared orthophoto (NAIP), and b) a very high-resolution satellite image (Maxar, Microsoft). Note that the *silva2016* algorithm identified many of the small tree crowns visible in the middle of these orthophotos.

$$CC = \frac{\text{Crown area}}{\text{Total area}} \times 100 \quad (1)$$

Here, where *CC* is the canopy cover, ranging from 0 to 100 (%), *Crown area* is the sum of the crown areas in a mapping unit (i.e., measurement plot, forest stand, or 30 m grid cell), and *Total area* is the size of the corresponding mapping unit.

Summary statistics tables for the field measurement plots and forest stands were used to estimate CC for individual plots and stands. A *Join* operation between the gridded GIS layer and the summary statistics table based on the feature identification number (FID) field. The workflow in Fig. 3 describes the entire process of the CC map creation resulting in the 30 m grid cell GIS layer.

2.4.2. Procedure #2 (Area-based)

This analytical procedure was designed as a raster alternative to the vector-based method proposed in Procedure #1. The denoised point clouds were managed in ArcGIS Pro 3.0. The point-cloud data was first converted to a 2 m spatial resolution raster GIS layer to obtain a continuous CHM layer. The CHM layer was then reclassified using a height threshold of 3 m above ground level, where pixels representing <3 m were coded as “0”, the rest were coded as “1”. The result of the reclassification was a raster GIS layer with two classes, representing tree crowns (1) and forest openings (0) (Fig. 4).

ArcGIS Pro's *Zonal Statistics* were applied using the plot, stand, and grid borders as feature zone data. The *mean function* was used to calculate the average code values within these borders. Subsequently, the averaged values were directly converted to a CC value by multiplying them by 100. For example, sample plots with a 404.6 m² fixed area contain about 100 pixels (pixel size = 2 m). Assume that 80 out of 100 pixels represent tree crowns while the rest do not. In this case, a CC value of 0.80 was estimated which would be the CC estimate of the sample field measurement plot in percentage terms (e.g., 80%). The same calculation was applicable to the stand and grid cell GIS layers, as well. The development of the grid cell GIS layer was necessary for creating a continuous map product as previously described in Procedure #1. Like Procedure #1, a *Join* operation was performed between the original grid layer and the summary statistics table based on the FID field.

2.4.3. Aerial image interpretation

An aerial image interpretation process based on expert knowledge was employed to estimate CC for the 255 fixed area, field measurement plots. USDA NAIP imagery was used to estimate CC for each plot. CC was estimated by two experienced photo-interpreters. One interpreter is a forest engineer (the 1st author of this MS), while the other is a remote sensing and GIS professional experienced with forest research (the 2nd author). The interpreters carefully assessed the NAIP imagery contained within the boundaries of field plot polygons on a computer screen at a scale of 1:1,000 using ArcGIS Pro. Their assessments were made independently, and each plot was given a CC estimate that ranged from 0 to 100% in 5% intervals. After the first assessment, the estimations made by the two persons were compared, and the inconsistent estimates (i.e., where CC differed by more than 10% in the two estimates) were assessed again by the interpreters together; this time, potential reasons for disagreement were discussed, and a final estimate was made jointly.

2.5. Accuracy assessment

The accuracy assessment of CC estimates relied on an established plot/grid sampling method once proposed by the Climate Action Reserve (Nickerson, 2014) and employed in a study by Ucar et al. (2016). In the plot/grid sampling method, a systematic grid of points is generated within the boundary of each field measurement plot polygon (404.6 m², 0.1 ac). In this case, a grid of 121 points located within each plot, with a spacing of 1.81 m between the points, was overlaid on the

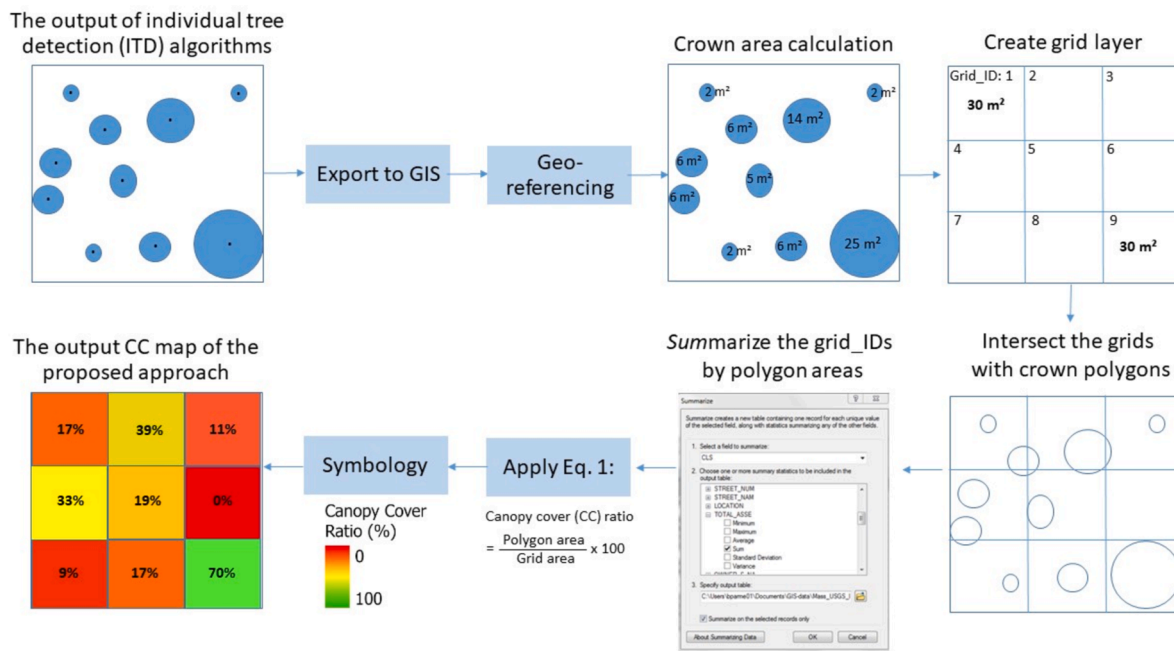


Fig. 3. A demonstration of the proposed CC estimation method, resulting in canopy cover map with a CC value interval of 0–100%. The same method is also applicable to the area-based procedure with minor changes. In this case, the *Intersect* operation would be replaced with *Zonal Statistics* to calculate the area of crown pixels within each grid.

2021 NAIP imagery (Fig. 5). Each point was estimated as representing tree cover over the ground (1) or not (0) by the author of the Ucar et al. (2016) study. The proportion of points representing tree cover in relation to the total number of points in each measurement plot resulted in an estimate of CC for the plot. This process employed the same USDA NAIP aerial imagery as used in other parts of this work. This reference dataset should contain less potential subjectivity that might be associated with the more general aerial photo-interpretation effort (van Laar and Akça, 2007) noted in section 2.4.3.

3. Results

The results of the Procedure #1 analysis indicated that at the three different scales (measurement plot, forest stand, or landscape) the average CC was 83–85%, with standard deviations ranging from 17 to 22% (Table 1). The highest CC, in general, was observed in areas dominated by pure loblolly pine and mixed white oak-red oak-hickory forests. As one may expect, non-forest areas, such as roadways, ponds, and rights-of-way, had the lowest CC due to a general lack of tree-like vegetation. Roadless and wilderness areas were easily distinguished in the northern and central areas of the study area (Fig. 6). Recent timber and fire management activities were also apparent, as well as tornado events. At the tree level, the silva2016 algorithm (Procedure #1) detected 28,772,013 tree crowns across the study area, indicating an average density of 307 trees/ha. However, a comparison with field data measured from 255 plots revealed an average density almost double this estimate. Interestingly, tree crown areas calculated by Procedure #1 ranged in size from 0.1 to 1,161 m², with an average of 40.7 m², and it became evident that unreasonably small and large crown sizes were a result of overlapping tree crowns, which were identified as one large crown by the silva2016 algorithm. The results of the Procedure #2 analysis indicated that at the three different scales (measurement plot, forest stand, or 30 m grid) the average CC was 81–89% with standard deviations ranging from 23 to 39% (Table 1). The range of mean CC is therefore wider under Procedure #2, as are the variation in CC estimates. The visual assessment using aerial image interpretation methods yielded a mean CC estimate of about 76% within the 255 field

measurement plots, with a corresponding standard deviation of about 22%. The reference dataset, using an established plot/grid sampling method, yielded a mean CC of about 74% and a standard deviation of about 21%. Therefore the reference dataset produced lower CC estimates than the analytical procedures.

Using current timber sales records, we focused on eight stands (sub-compartment areas) which were applied a final harvest (clearcut) in 2019 and 2020, 2 years before LiDAR data acquisition. The CC estimates from Procedure #1 in the final harvest areas ranged between about 6% and 43%, with an average of 24% (Table 2). The reason for a CC estimate above 40% in these areas was due to the silvicultural method employed (seed tree harvests), where some live trees were retained within the final harvest areas for natural regeneration purposes (Fig. 7). Since Procedure #1 is individual tree-based, the number of seed trees and tree density of those sub-compartment areas can be detected from the underlying layers of the CC map. Table 2 indicates that the live tree density within recently harvested stands was about 77 trees/ha, on average.

The accuracy of the two analytical procedures and the more general aerial interpretation method was based on 255 reference plots where the plot/grid sampling method was employed. According to our results, the area-based procedure (Procedure #2) performed slightly better than the individual tree-based procedure (Procedure #1), as the Pearson's correlation coefficient was 0.89 in the former case as compared to 0.79 in the latter (Table 3). In all three cases, there was a positive and very strong correlation between CC estimates and reference data ($p < 0.01$). The correlation between the Procedure #1 and Procedure #2 was also high ($r = 0.83$), in part due to the same height threshold applied to the CHM (i.e., 3 m above ground level). The more general aerial interpretation method yielded an RMSE of 10.9%, and its correlation coefficient (with respect to the reference data) was close to that of Procedure #2 ($r = 0.87$, $p < 0.01$). Although the results of the conventional method seem better, this method may be inapplicable across broad areas because a visual assessment of the CC would require an extensive amount of human effort.

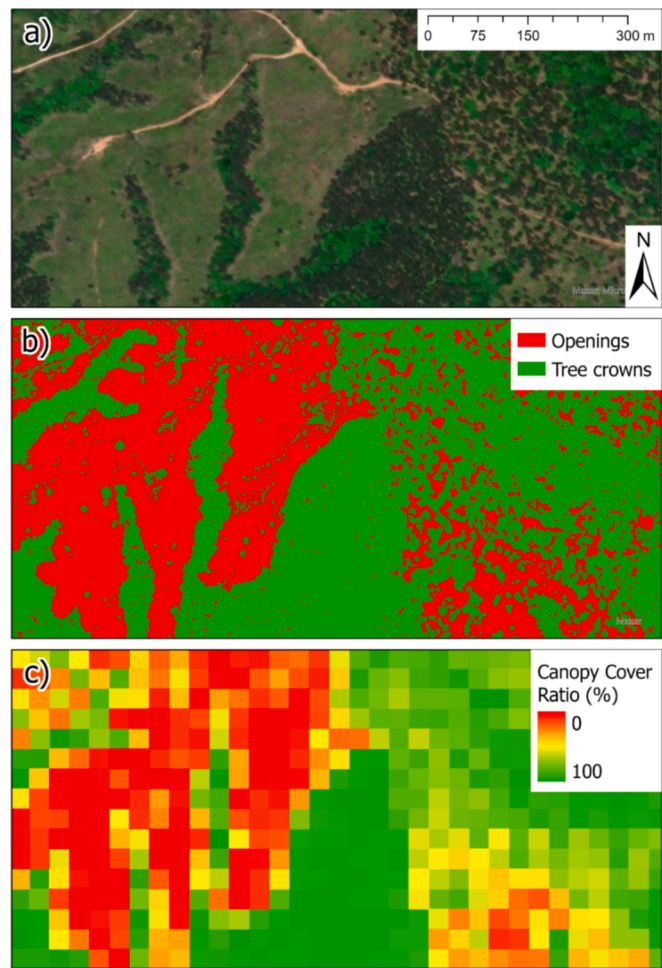


Fig. 4. A portion of the study area exhibiting nearly full CC and lower levels of CC within forest openings. Very high-resolution satellite imagery (a), classified raster layer (b), and gridded CC estimate layer of the same area (c) (Basemap source in (a): Esri).

4. Discussion

In the present study, we developed a framework for spatial modeling of CC in a large, forest-dominated landscape using airborne LiDAR data. LiDAR-based area and individual tree crown segmentation (i.e., analytical) procedures were described and both helped to create fairly accurate CC maps (RMSEs of 15% and 16%). The average CC at the landscape level was between 81.4% and 83.6%, which is slightly higher than the reference dataset, perhaps because the LiDAR data can indicate the presence of smaller trees more effectively than the human eye can distinguish them in an aerial image. In [Qiu et al. \(2018\)](#), a maximum permissible error rate is reported as 15% for forest canopy estimates. Given this potential standard, and the fact that our study area contained vast non-homogeneous natural forests, our map accuracy seems acceptable for use in most operational management and landscape-level inventory applications.

The difference between the landscape-level average CC estimates (by both procedures) and the plot-level reference dataset can partially be attributed to the location of the sample plots, which were all situated within ‘operable’ areas. However, there were some parts in the landscape deemed ‘inoperable’ due to certain constraints such as steep slopes, roadless areas, wilderness areas, and riparian zones ([U.S. Forest Service, 2004](#)). Management activities, including harvesting and prescribed burning, are responsible for lower CC estimates in the operable areas. Also, the impacts of recent natural disturbances can be recognized

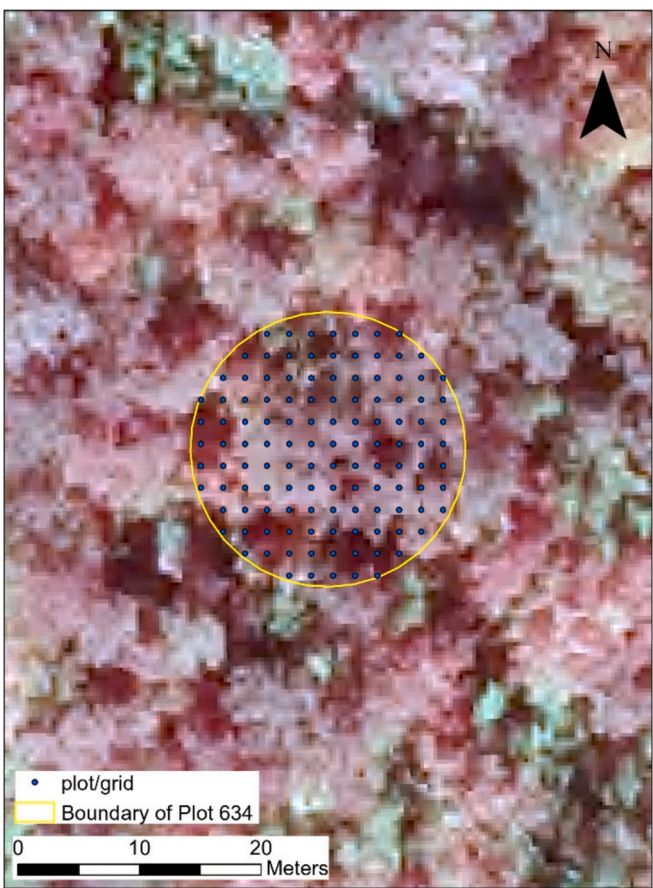


Fig. 5. Description of the plot/grid sampling method over Plot 634.

Table 1						
Descriptive statistics for canopy cover (%) estimated by various procedures.						
Procedure	Scale	N	Min.	Average	Max.	Standard dev.
Procedure #1 (LiDAR, individual tree-based)	Plot	255	4.6	83.1	100	21.6
	Stand	6852	0	85.4	100	17.2
	Landscape	1	0.02	83.6	100	21.7
Procedure #2 (LiDAR, area-based)	Plot	255	0	85.0	100	22.7
	Stand	6852	0	88.9	100	23.6
	Landscape	1	0	81.4	100	38.8
Visual assessment (based on NAIP)	Plot	255	0	75.7	100	21.7
The plot/grid sampling method (based on NAIP, REFERENCE)	Plot	255	5.0	74.3	100	20.8

through the procedures described here. The Jacksonville Tornado touched the northern part of the study area on March 19, 2018, damaging 2,294 ha of forests ([U.S. National Weather Service, 2018](#)). For a small part of the study area, recovery after the tornado event through 2021 can partly be explained by the CC estimates in this area, as thinning-like disturbances in CC estimates may be detectable with bi-temporal airborne LiDAR measurements ([Arumäe et al., 2020](#)).

Among large-scale projects, [Mahoney et al. \(2018\)](#) estimated CC in the Northwest Territories of Canada using both airborne and spaceborne LiDAR (Geoscience Laser Altimeter System) datasets relying on the

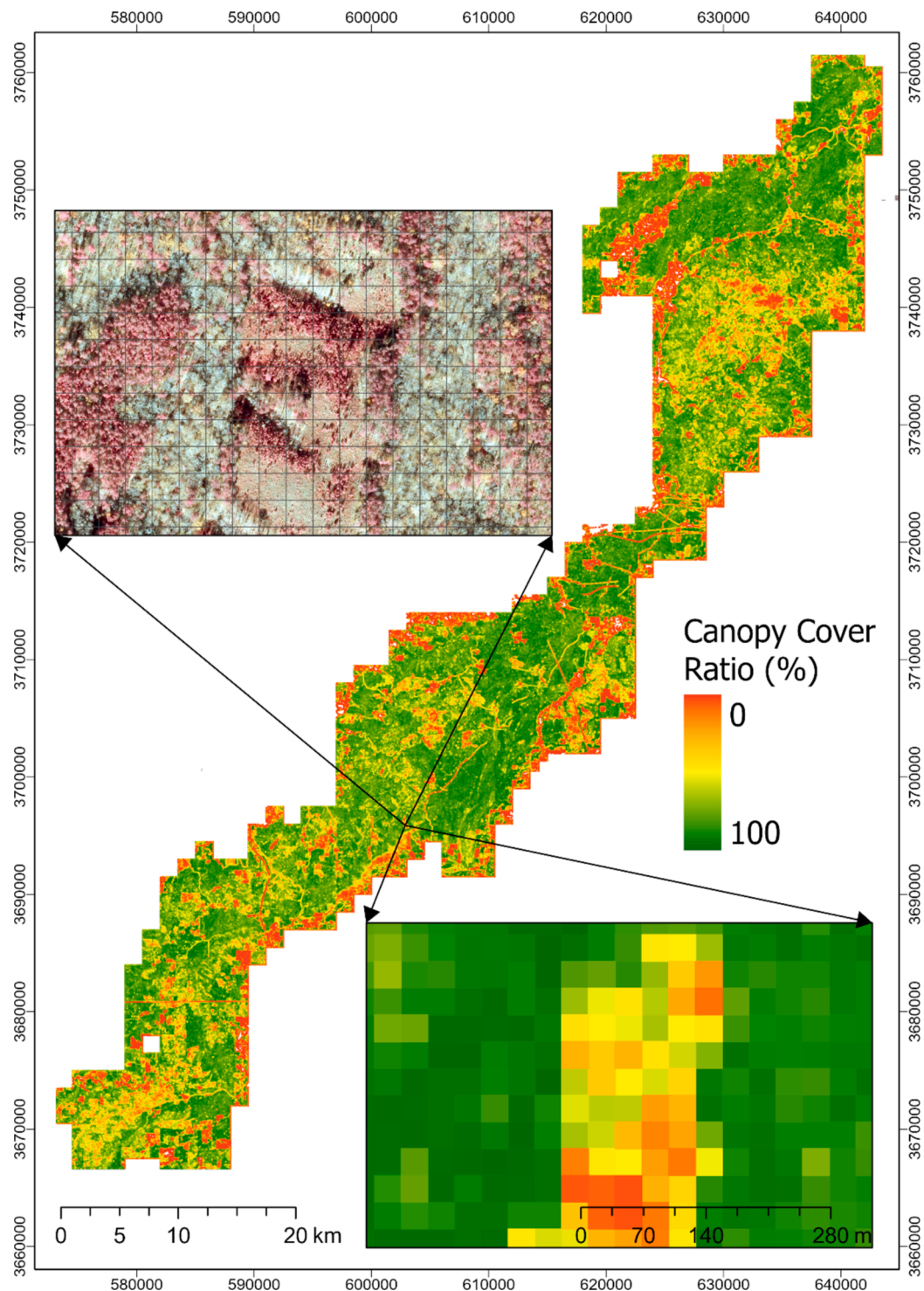


Fig. 6. Canopy cover map of the study area, with roads, powerlines, and small regeneration sites detectable through low CC estimates.

relationship between tree height and tree crowns. The results revealed an average CC ranging between 20% and 70% across the region and the RMSE was 9%. The relatively high accuracy of the CC estimates may be attributed to relatively homogeneous characteristics of boreal forests and/or ignoring additional error sources embedded into the allometric models used (i.e., the tree height-crown length relationship). In another project, Akturk et al. (2023) estimated CC of forests in Turkey (about 23 million ha) using freely distributed spaceborne LiDAR (ICESat-2/ATL08) and Landsat imagery. The results showed that more than half of the country's forestland fell into the dense CC class (CC > 70%). The

researchers reported an average map accuracy of about 80% which varied depending on using strong or weak beams of the ICESat-2 product. Because of the non-continuous (sample-based) nature of spaceborne LiDAR products, additional remote sensing sources are often needed to estimate and map CC of the areas outside of LiDAR coverage. While employing multi-source approaches are inevitable to create large-scale maps, this adds complexity to the models developed, which may hinder the uptake and practicability of such applications by the forestry community.

Stojanova et al. (2010) estimated CC for a large, vegetated area

Table 2

Information on the stands harvested in 2019 and 2020. Procedure #1 was implemented for canopy cover and tree density estimates.

Compartment and stand number	Area coverage (ha)	Canopy cover (%)	Tree density (tree/ha)
279–4573	4.7	17.5	74
93–1713	19.0	43.3	59
88–3430	3.2	22.4	89
88–1456	4.6	12.3	57
88–5008	4.3	27.1	89
88–687	4.8	6.0	48
273–3716	7.7	36.9	122
87–5630	4.7	22.9	82
Average	6.6	23.6	77

(72,226 ha) composed of diverse tree species in eastern Slovenia. While the accuracy rates of this work were similar to our work, the method and data used were quite different as they integrated Landsat imagery with airborne LiDAR due to the limited area coverage of airborne LiDAR in that time. Today, the cost of LiDAR data is more affordable, and one can access spaceborne LiDAR data free of charge, resulting in larger coverage, greater data availability, and multi-source remote sensing projects (Coops et al., 2021). Nevertheless, point cloud density of spaceborne LiDAR systems may not be adequate for CC analysis when used alone.

At smaller scales, CC can be estimated and mapped with greater detail using close-range LiDAR data, without a need for additional remote sensing sources. Pu et al. (2023) described an automated way of detecting and segmenting individual trees using UAV-based LiDAR for a poplar plantation in China. The authors provided no information on CC values of their study area but relatively high accuracies (i.e., > 90%) were reported for tree detection and crown delineation results. Nevertheless, some researchers have pointed out that obtaining high accuracy rates may be difficult in structurally complex, natural forest areas without manual interventions (e.g., exploring optimal window size, fine-tuning in algorithms) to the automated processes (Vatandaşlar and Zeybek, 2021; Gao et al., 2022). For example, the results of a LiDAR-aided forest inventory study suggested that the deviations in CC estimates from reference data could be as high as 21.8% in certain natural forest plots, even if terrestrial-based, close-range laser scanners are used (Vatandaşlar and Zeybek, 2021).

Visual (manual) assessment of CC based on optical imagery (e.g., USDA NAIP imagery) is still a common method among foresters, ecologists, and landscape planners (Jennings et al., 1999; van Laar and Akça, 2007; Jiang et al., 2017; Turkish General Directorate of Forestry, 2017). In order to evaluate the reliability of this method, we compared visually assessed CC estimates in 255 field measurement plots against a reference method (Ucar et al., 2016). While the correlation between the two methods was positive and strong ($r = 0.87$, $p < 0.01$), RMSE was found to be 10.9% (Table 3). The visual assessment method slightly overestimates the average CC compared to the plot/grid sampling method (Table 1). These results suggest that using visual assessment data as a reference may be misleading for accuracy assessments of CC estimates in natural forests. In the context of forestry research, the permissible error rate is often reported as about 10% for field inventory reference data (Hyypä et al., 2020). Another study obtained slightly stronger correlations between the aerial imagery and eye-level photography-based CC assessments (Jiang et al., 2017), but it was conducted in an urban greening setting, often demonstrating more homogeneous structure than natural forests. Still, field visits, rather than a reliance solely on aerial images, were recommended for most reliable CC estimates, particularly in medium to high density forests.

A comprehensive work by Coops et al. (2021) described studies modeling forest attributes using LiDAR technology. Although the quantity of studies focusing on CC is much less compared to other forest attributes, such as volume, aboveground biomass, and forest height, CC

estimates were found to be more consistent. Most findings reviewed for this discussion suggest that our map and its estimation accuracy are comparable to the studies with similar scope in the literature. Considering the large and structurally complex landscape of the study area, we conclude that the resolution and accuracy of the CC estimates seem sufficient, suggesting the proposed procedure (Procedure #1) here can be applicable not only for CC assessments but also for varied resource management and planning tasks.

4.1. Management implications

Some public agencies in the United States are actively restoring the forest habitats of endangered species, such as the red-cockaded woodpecker (RCW) (U.S. Fish and Wildlife Service, 1973; Stober et al., 2020). RCWs typically require mature and open longleaf pine forests for nesting and roosting habitat (Smart et al., 2012; Brown and Ferguson, 2019). Thus, identifying, monitoring and protecting such forest structure is critically important to maintain and increase existing RCW populations in the study area. In an effort to understand optimal canopy conditions for the RCWs, 143 known actively-used and inactive cavity trees within the study area were buffered in GIS by a distance of 40 m, as vegetation composition is crucial between 17 and 66 m for RCWs (Smart et al., 2012). Then, the buffered areas were intersected with our grid-based CC map. We found that CC varied between 21.5% and 92.0% across the 143 sites, with an average CC of 64.4%. We observed that CC within active nesting sites was generally less than 50%. This information is important for species distribution models, as CC is reported as the most powerful contributor to a model's goodness-of-fit among LiDAR-derived metrics (Smart et al., 2012). Indeed, RCW modeling studies recently have gained more attention from wildlife and conservation planning communities (i.e., Lucash et al., 2022; DuBose et al., 2023). Further analyzing longleaf pine stands with similar CC estimates across the study area may help forest managers identify RCW habitat.

Another example involves a large-scale disturbance event mentioned earlier, the Jacksonville Tornado, which occurred in 2018. The EF-3 tornado crossed the northern part of the study area from west to east, resulting in many thousands of windthrown trees and broken stems (U.S. National Weather Service, 2018). While the damages in settlements, private lands, and highways were relatively well-documented, the effect of the tornado on the study area is to this point unknown. To this end, we intersected the published tornado track with our grid-based CC map (Fig. 8). It was observed that 2,294 ha of the study area was affected by the event, and the average CC of this area decreased to 64.8%, although there was a 3-year gap between the dates of the disturbance and LiDAR data acquisition. An analysis of the CC estimates inside and outside of the track of the tornado might help forest managers better understand the relative scale and magnitude of this disturbance from a forest management perspective. Fig. 8 also suggests that a significant amount of forest cover within the track of the tornado was not disturbed at all. Using the average CC of the study area as a threshold (i.e., 81.4%), 778 ha of forestland (ca. 40% of the published area of the tornado track) seemed to be undisturbed by the event (i.e., CC > 81.4%). Therefore, the boundaries of the tornado track might be revised by considering the disturbed sites using a CC map such as the one presented in this study. Moreover, surviving trees can be detected based on the underlying layer (i.e., silva2016 polygons) used in Procedure #1, as shown earlier in a different context (see Table 2). A similar analysis may also be applied to other stand-replacing disturbances, such as wildfires, beetle outbreaks, and climate-induced forest diebacks. In this way, potential areas to be restored and the number of trees to be planted can be calculated with moderate accuracy levels if disturbed areas need to be reforested.

Finally, we assessed CC within unmanaged areas across the study area. There are 23 areas, having 17,386 ha of land area in total (about 19% of the study area), that are not being actively managed by the U.S. Forest Service for various reasons (e.g., land being designated as wilderness, land lacking a road network, and land acting as a sensitive

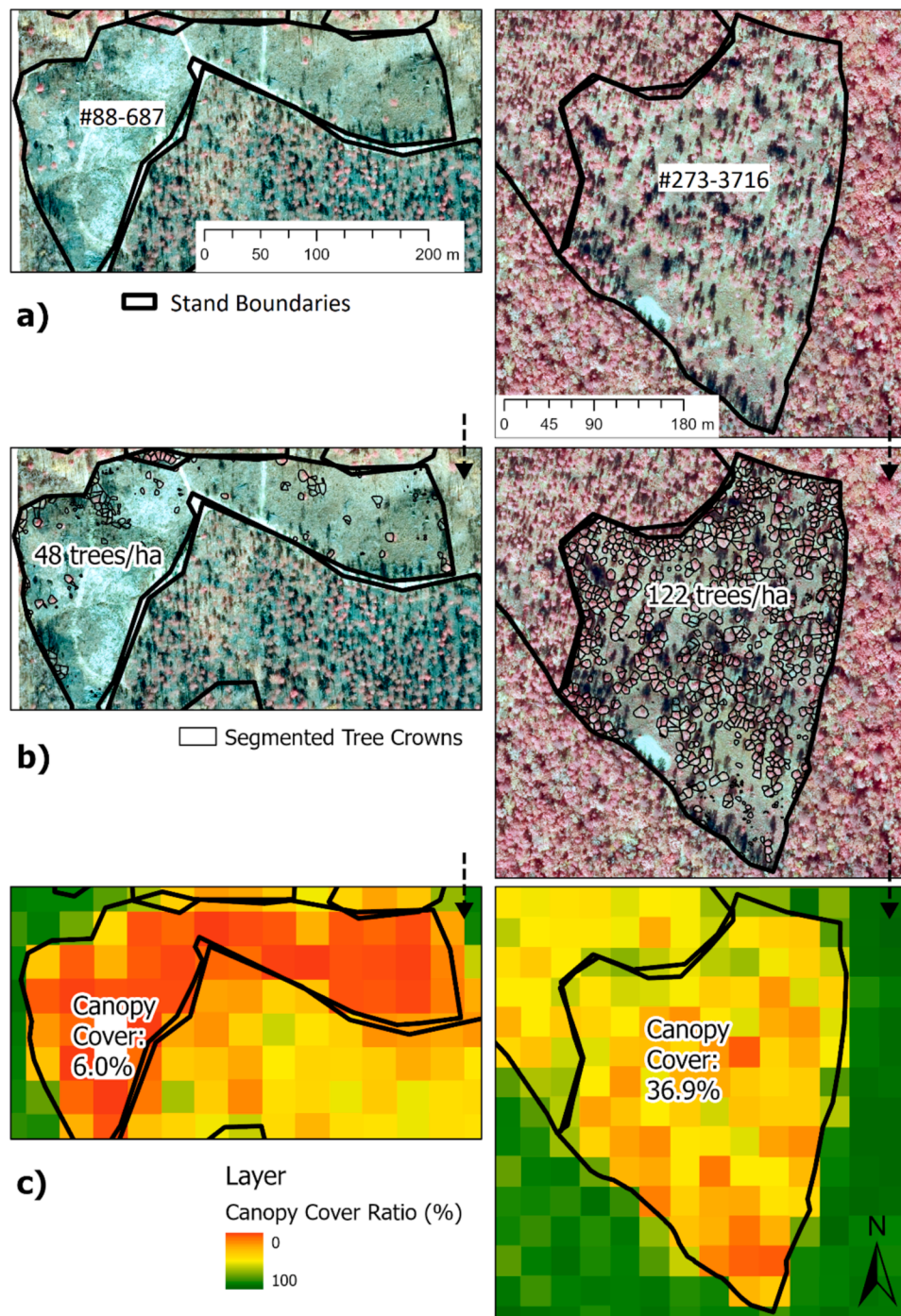


Fig. 7. Views from intensively (#88-687, left) and extensively (#273-3716, right) harvested stands within the study area. Stand boundaries overlaid on a near infrared orthophoto (a), individual tree crowns vectorized within the stand boundaries (b), and CC estimates of those stands (c). Procedure #1 was implemented for map production.

viewshed). Since forest cover in these areas has been mostly unchanged over the last 50 or 60 years, the average CC in these areas was approximately 10% higher than the entire study area. The wilderness area had the highest CC estimate (98.8%), while viewshed had a lower CC estimate (72.2%), approximately 10% lower than the study area average.

As partially demonstrated in this work, there are a number of issues in natural resource management where CC maps can be used. In addition to the aforementioned examples, appropriate CC maps may help assess restoration success in reforested or afforestation areas (Yıldız et al., 2022), may be useful for updating the cover management factor for soil

erosion models (Yücesan et al., 2019), may reveal the efficiency of prescribed burning activities (Stober et al., 2020), may help identify potential hotspots for carbon stocking (Yücesan et al., 2019), and may help determine the recreation suitability of forests (Caglayan et al., 2020).

4.2. Limitations

The data, methods, and products provided in the present study are capable of producing reasonable CC estimates and are useful for diverse management-related applications. However, some problems may arise

Table 3
Pearson’s correlation coefficients (r) and RMSE values for canopy cover estimates by various procedures (plot-level).

Procedure	Procedure #2 (LiDAR, area-based)	Visual assessment (based on NAIP)	The plot/grid sampling method (based on NAIP, REFERENCE)	RMSE (%)
Procedure #1 (LiDAR, individual tree-based)	0.83*	0.75*	0.79*	16.0
Procedure #2 (LiDAR, area-based)		0.88*	0.89*	15.0
Visual assessment (based on NAIP)			0.87*	10.9

*Correlation is significant at the 0.01 level (2-tailed).

regarding data availability and reliability, which will limit its uptake and practical use at different scales. For example, airborne LiDAR data, the primary data source for this study, were collected in the context of a flight mission funded by the U.S. Geological Survey. However, airborne LiDAR data may not be available in undeveloped and developing countries due to high costs and/or data policy issues (Jiang et al., 2017; Coops et al., 2021). Even in developed countries, including the U.S., all land areas are not covered by airborne LiDAR. Therefore, lower-cost data and methods, such as drone-based imagery (Yurtseven et al., 2019), structure-from-motion (Zeybek et al., 2023), LiDAR-equipped smartphones (Gülci et al., 2023) might be necessary to create digital

point clouds comparable to airborne LiDAR. Unfortunately, these tools and methods are inappropriate for broad scale landscape assessments. Similarly, recently captured, high-resolution, and color-infrared digital aerial photography, which served as our reference, may not be readily available in certain parts of the world. While the images we used were captured through the U.S. Department of Agriculture NAIP program and are freely distributed via the Internet, this is not the case in many parts of the world. Even if available, the cost of high-resolution images in large quantities to cover broad areas may be prohibitive (He et al., 2021). Such problems have the potential to hinder the uptake of the procedures described here, which in turn may limit the scalability or extension of this work.

At a local scale, we observed inconsistent crown segmentations in certain regions of our study area which might limit the use of Procedure #1 (individual tree-based) in precision forestry work. While it is technically impossible to detect small trees growing under large canopies by the silva2016 algorithm (Silva et al., 2016), other features were incorrectly delineated. For example, some forest openings appeared as if they were covered by mature tree crowns (Fig. 9). Another problem with the algorithm employed in Procedure #1 was the delineation of multiple crowns as if they belonged to one large tree. It appears that the 2.2% difference between the average CC estimated by Procedures #1 and #2 may have been caused by this algorithmic limitation. Therefore, researchers using the individual tree-based procedure should be cautious when they analyze tree density in disturbed forest sites. This problem confirms a statement in Adhikari et al. (2023) “... applying an individual tree-based approach in complex stands such as uneven-aged natural forests and plantations with high stem density is difficult (p. 2).” Nevertheless, we did not observe crown polygons overflowing over buildings or other

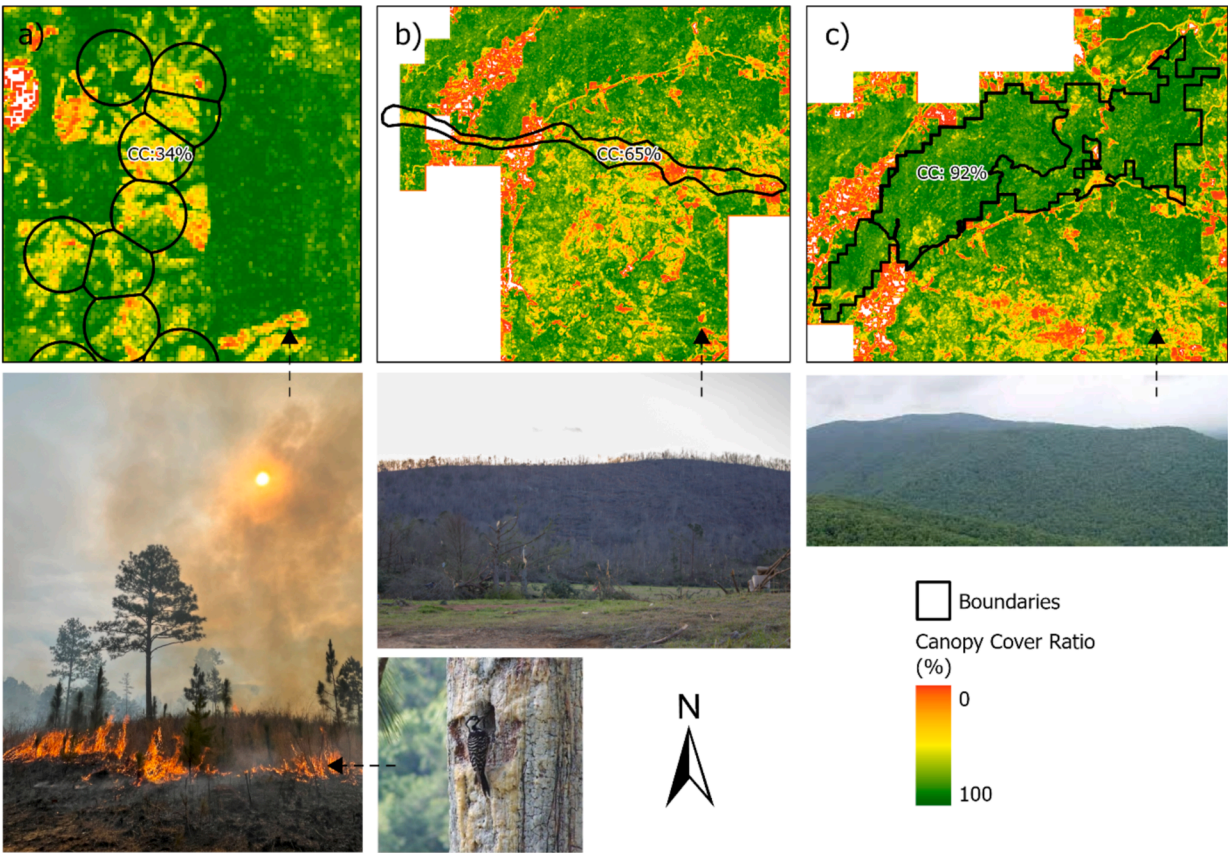


Fig. 8. Management-related tasks within the study area where the utilization of a CC map may be beneficial: Assessing the optimum habitat requirements of red-cockaded woodpeckers (a), evaluating the relative scale and magnitude of damage by the 2018 Jacksonville Tornado (b), investigating the differences in forest cover between managed and unmanaged forest areas (c). While the photograph depicting the tornado’s damage path over the mountain (in the middle) was sourced from the U.S. National Weather Service (2018), other photographs were from U.S. Forest Service.

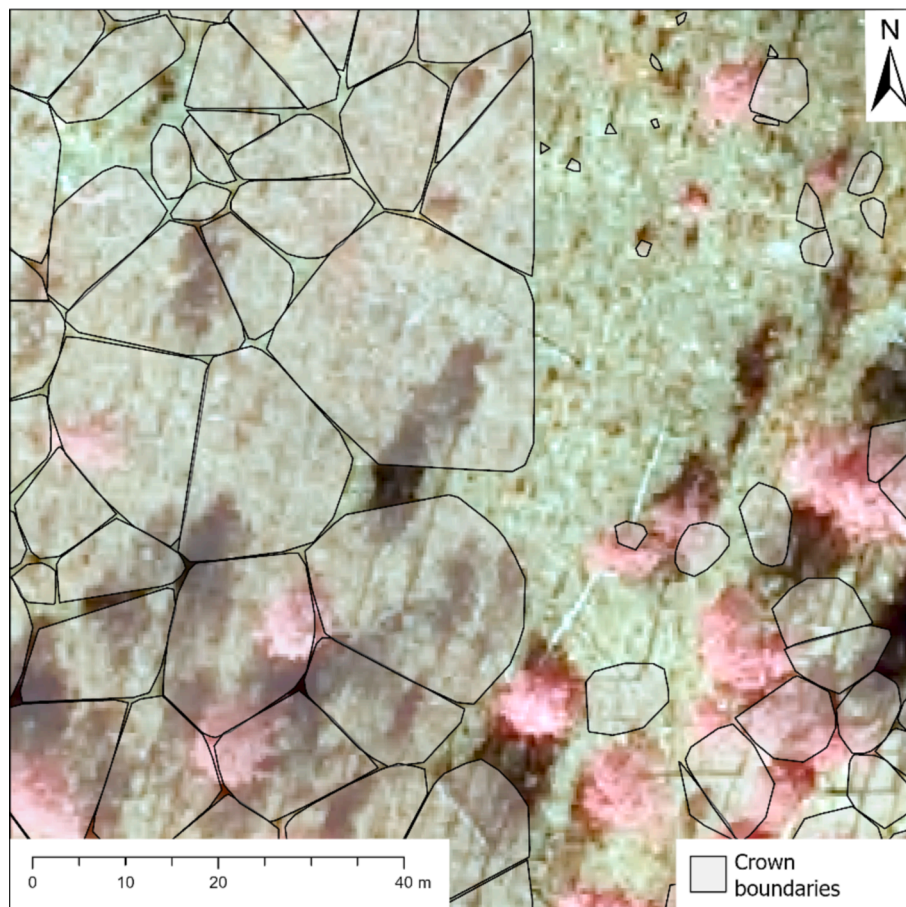


Fig. 9. An open forest site incorrectly delineated as if it is covered by tree crowns across most of the left-hand side of the image. Although uncommon, such issues can occur when dealing with overlapped LiDAR tiles.

manmade structures, unlike those encountered by [Henn and Peduzzi \(2023\)](#). The conflicting findings obtained by applying the same algorithm in our study may be attributed to a difference between the studied environments (urban vs. natural forest). Thus, the performance of the *silva2016* algorithm seems acceptable in forest-dominated landscapes.

One broad-scale map product produced in this study has a 30 m spatial resolution, which may be viewed as insufficient for small-scale analyses. However, we chose this resolution with both pragmatic and scientific considerations. The study area is vast (93,694 ha), and the land surface is represented by more than 1 million grid cells at this scale. Since our underlying layers have a finer spatial grain for both procedures, creating a higher resolution map is always possible. In this case, the data processing and handling would be more time-consuming. Even with the current resolution, displaying the symbolized CC layer of the entire area takes several minutes in GIS software (yet is a function of graphics card capabilities). More importantly, there is evidence in the scientific literature suggesting that higher-resolution products do not necessarily result in more reliable outcomes. A recent study by [Atkins et al. \(2023\)](#) investigated the optimal resolution of airborne LiDAR-based maps examined eight LiDAR-derived metrics, including CC, at several spatial grains from 5 to 1,000 m in distinct forest types. The results indicated that a smaller “*representative elementary area (REA)*” was needed for accurate characterization of CC in evergreen needle-leaf forests. Specifically, an REA between 25 and 75 m was found to be appropriate to sufficiently estimate CC regardless of the forest type.

The maps, tables, and assessments in the present study provide only a snapshot of the study area taken at a single point in time. However, forests are highly dynamic ecosystems with their vertical and horizontal structures are constantly evolving. CC estimates for certain portions of

the study area may have undergone significant changes since our 2021 LiDAR data acquisition due to recent anthropogenic activities, such as timber management and prescribed burning activities, and natural events such as wildfires, insect outbreaks, and windthrow. Therefore, monitoring the spatiotemporal changes in forest ecosystems is essential not only for understanding forest dynamics but also for (inter-)national reporting schemes ([Food and Agriculture Organization of the United Nations, 2020](#); [Coops et al., 2021](#)).

5. Conclusion

In this study, a framework was presented for creating CC maps using only airborne LiDAR data. The framework deliberately avoided off-the-shelf LiDAR (canopy) metrics that might be primarily related to canopy density rather than CC estimates. Instead, an ITS algorithm, *silva2016*, was employed and a proposed area-based procedure was used to characterize CC. In addition, we demonstrated how CC maps could be converted to an interval of 0–100% in GIS, making it more instrumental for diverse ecological assessments. Finally, the accuracy of the procedures was assessed using the outcomes of an established plot/grid method as a reference. Accordingly, RMSE values for the individual tree- and area-based procedures were found to be 16.0% and 15.0%, respectively.

Our conclusions are as follows: (i) both individual tree- and area-based procedures based on LiDAR data are capable of creating sufficiently accurate CC maps for large, natural forestlands, (ii) while the ITS algorithm (*silva2016*) generally performed well in delineating individual tree crowns, the results are limited for extending the outcomes to tree density estimates, and (iii) using aerial interpretation methods that are solely based on aerial images (i.e., NAIP in our case) may produce

similar estimates of CC as the two analytical procedures described here, but aerial interpretation methods are limited in their application across broad areas.

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CRediT authorship contribution statement

Can Vatandaslar: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Taeyoon Lee:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Pete Bettinger:** Writing – review & editing, Validation, Investigation. **Zennure Ucar:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Jonathan Stober:** Writing – review & editing, Writing – original draft, Validation, Data curation. **Alicia Peduzzi:** Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Can Vatandaslar reports financial support was provided by US Department of Agriculture Forest Service. 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.

Data availability

Data will be made available on request.

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A conference paper (abstract) consisting of some of the preliminary findings from this project has been accepted for the International Union of Forest Research Organizations (IUFRO) World Congress. It will be presented as an e-poster at Session T5.1: Artificial Intelligence in Forest Biometry in June 2024. Nevertheless, the present manuscript includes significant changes and complete findings from the project.

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