

Article

Semi-Automatic Stand Delineation Based on Very-High-Resolution Orthophotographs and Topographic Features: A Case Study from a Structurally Complex Natural Forest in the Southern USA

Can Vatandaslar ^{1,2,*} , Pete Bettinger ² , Krista Merry ² , Jonathan Stober ³ and Taeyoon Lee ⁴ 

¹ Faculty of Forestry, Artvin Coruh University, Artvin 08100, Turkey

² Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA 30602, USA; pbettinger@warnell.uga.edu (P.B.); kmerry@warnell.uga.edu (K.M.)

³ U.S. Forest Service, Talladega National Forest, Heflin, AL 36264, USA; jonathan.stober@usda.gov

⁴ Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX 77843, USA; taeyoon.lee@ag.tamu.edu

* Correspondence: canvatandaslar@artvin.edu.tr

Abstract: In the management of forests, the boundaries of individual units of land containing similar forest resources (e.g., stands) are delineated and used to guide the implementation of management activities. Traditionally, stand boundaries are drawn or digitized by hand; however, work recently has been conducted to automate the process using aerial imagery or airborne light detection and ranging (LiDAR) data as supporting resources. The work described here applies an object-based image analysis (OBIA) process to aerial imagery and to a landform index database. The size and shape of stands in the outcomes of these applications are then adjusted to conform to the desired product of land managers. These products are then intersected as they each contain information of value in the stand delineation process. The intersected database is then adjusted once again to conform to the desired product of land managers. Conformity of the size and shape of the resulting stand boundaries to a reference database drawn subjectively by hand was low to moderate. Specifically, the overall agreement for spatial and thematic (class names) accuracies was 43.0% and 56.8%, respectively. Nevertheless, the process of automating the stand delineation effort remains promising for achieving an efficient and non-subjective characterization of a structurally complex forested environment.

Keywords: GEOBIA; segment mean shift algorithm; landform index; visual interpretation; national agriculture imagery program (NAIP)



Academic Editors: Zhong Zhao and Nikolay S. Strigul

Received: 25 February 2025

Revised: 1 April 2025

Accepted: 9 April 2025

Published: 11 April 2025

Citation: Vatandaslar, C.; Bettinger, P.; Merry, K.; Stober, J.; Lee, T. Semi-Automatic Stand Delineation Based on Very-High-Resolution Orthophotographs and Topographic Features: A Case Study from a Structurally Complex Natural Forest in the Southern USA. *Forests* **2025**, *16*, 666. <https://doi.org/10.3390/f16040666>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In the field of forestry, management decisions are typically applied to stands of trees rather than to individual trees. A stand serves as the basic operational unit where various management practices, such as clearcutting, regeneration, and prescribed burning, are implemented [1,2]. A forest stand is defined as a contiguous community of trees, usually uniform in species composition and biophysical characteristics, such as canopy height, layering, and timber quality, which distinguish it from neighboring stands. At times, roads, streams, ridgelines, ownership boundaries, and other natural and anthropogenic features define the boundary of a stand of trees. Further, a stand may have a minimum or maximum size that adheres to data management and operational practice protocols. In this context,

a forested landscape can be viewed as a mosaic of thousands of individual stands, and effective forest management significantly relies on maintaining up-to-date stand maps to catalogue composition and structure, guiding management actions.

Forest managers tend to favor vector-based stand maps (using polygon features) over raster-based maps for several reasons. Vector-based stand maps often serve as the basis for understanding where forest management or contract actions will be implemented. Vector maps allow for the direct association of inventory data, such as tree diameter, species mix, density, volume, and other attributes, with geographic information system (GIS) feature records. Vector-based stand delineations also simplify tasks such as area calculation and database editing while requiring less computer memory. In addition, in many instances vector features more accurately represent the actual shapes and areas of stands compared to a collection of grid cells or pixels found in raster GIS databases.

In forest management planning, the current practice for generating vector-based stand maps involves manual digitization based on visual interpretation of satellite images or aerial photographs [3,4], perhaps supplemented with field-based collection of global navigation satellite system (GNSS) data. Commonly today, stand delineation is conducted as an on-screen (or heads-up) digitizing process, requiring the image interpreter to focus intently on a computer screen while identifying the edges of stands. This is a subjective process, and Hernando et al. [5] note that maps produced by different image interpreters may contain inconsistencies, though a validation process involving field surveys can significantly mitigate these accuracy issues [2,6]. In Turkish forestry, such maps, referred to as ‘draft stand maps’, are reviewed by planning experts before the forest inventory phase during the renewal of forest management plans. Errors in polygon boundaries or stand-type classifications are subsequently corrected, and the maps are finalized using ground truth data collected during inventory surveys [7,8]. Advances in geospatial tools and technology have enabled image interpreters and planning experts to produce non-subjective and potentially higher quality stand maps by leveraging high-resolution digital imagery and more precise ground data. Near-infrared (NIR) images are particularly valuable in this process, as they enhance the ability of an image interpreter to differentiate between various plant communities, such as those occupied by coniferous and deciduous forest tree species.

Forested landscapes span vast areas and often exhibit highly heterogeneous spatial structures. Delineating individual stands across thousands of hectares can therefore be an arduous and time-consuming task. This process is also influenced by the experience and skill of the analyst, introducing subjectivity, and reducing the repeatability of delineations [3,5,6]. Moreover, forests are dynamic ecosystems that undergo constant changes due to management practices and natural or anthropogenic disturbances. Consequently, in actively managed areas, stand maps often require updates every 5 to 10 years—although such revisions remain infrequent in many countries and are much more frequent in intensively managed landscapes. For instance, the stand boundaries of the Talladega National Forest in Alabama, USA, have not been updated in nearly two decades, yet the stand boundaries of nearby lands owned by large organizations such as Weyerhaeuser are updated continuously as management activities occur. Additionally, recent ‘mega fires’ have significantly reshaped forested landscapes in fire-prone regions [9]. For example, in 2021, Antalya Province in Turkey, located in the Mediterranean region, experienced a 10-day mega fire that burned approximately 55,000 hectares [10]. Such catastrophic events are becoming increasingly common in the region [9], underscoring the need for more frequent stand map updates. In response to these challenges, researchers over the past decade have focused on developing new tools and techniques to accelerate and automate the production of stand maps [1,2,4,11].

Object-based image analysis (OBIA) is a contextual classification technique that segments images by grouping small raster grid cells into vector objects. It is often preferred over raster-focused techniques (lacking the vector transformation) in stand mapping due to the ability to produce more meaningful results [12,13]. While OBIA can mimic a human's image interpretation skills [14], outputs are influenced by the choice of segmentation algorithms and the parameter settings defined by the user [5,15]. Furthermore, the consistency in the result of the mapping process depends on the quality of the input data. For instance, Hernando et al. [5] implemented a multiresolution segmentation algorithm to create a stand map of a Mediterranean forest (815 ha) in central Spain using digital orthophotography. Their map, compared with a manually delineated version, although subjective, was validated through field surveys and achieved an overall spatial and thematic accuracy of 65%. However, accuracy dropped to 31.8% for shrub stands due to mathematical confusion with the characteristics of high pole-wood classes.

Light Detection and Ranging (LiDAR)-derived data offers valuable insights into the vertical structure of a forest, and when combined with optical sensor data (natural light, infrared, etc.) that captures spectral information, which can aid in identifying tree species or species mixture, it may provide opportunities for developing more efficient and effective stand maps. For instance, Ozkan et al. [11] used the forest characteristics provided by airborne LiDAR data with the forest characteristics provided by WorldView-3 satellite imagery to produce stand maps for forest management in a 2172 ha mixed forest in northwestern Turkey. Their map, comprising 14 stand types, achieved an overall accuracy of 50%, which improved to 61% when similar stands were merged into 9 classes. Some researchers highlight the scarcity of multi-class mapping over large areas [16] and the reliance on subjective accuracy assessment protocols [1]. For instance, Sanchez-Lopez et al. [1], using LiDAR data, mapped a 54,000 ha area in northern USA by subjecting airborne LiDAR data to a multiresolution segmentation algorithm to delineate stands in even-aged forests. Instead of overall accuracy metrics, they modified spatial measures based on overlapping stand polygons and reported good agreement with reference data, although results were less reliable in undisturbed forests.

These findings suggest that the structural complexity of a forest has a greater influence on the accuracy of the outcome from automated stand mapping than the choice of input datasets or algorithms. However, a further challenge lies in meeting the specific requirements forest managers often impose on stand delineation efforts. These requirements may include a minimum area constraint, smooth stand borders resembling human-delineated maps, compact stand shapes, and the use of natural or anthropogenic linear elements (e.g., roads, creeks, ridges) to delineate stands. As a result, complex GIS procedures applied to diverse GIS databases are often required after the generation of stand boundaries through an automated process, preventing the overall mapping process from becoming fully automated. Such requirements are typically subjective and may vary from one forest planning unit to another. This may explain why recently popularized deep learning models are barely employed in forest stand delineation work. While convolutional neural network (CNN), U-Net, and You Only Look Once (YOLO) models are commonly used for individual tree crown (ITC) delineation, they are not currently utilized for stand delineation tasks in operational forestry.

The objective of this study is to develop a semi-automated methodological pipeline for producing stand maps for a broad, structurally complex forest in northern Alabama (USA). The process utilizes orthophotographs and landscape topographic features with the motivation of producing a stand boundary database that will support forest management planning efforts. We aim to fill a research gap by identifying an appropriate combination of input datasets, segmentation algorithms, parameter values, and GIS procedures applicable

to natural oak-hickory-pine systems. The rest of the manuscript is structured into six main sections: Section 2 describes the study area, data sources, and preprocessing steps. Section 3 details the OBIA method, mean shift segmentation algorithm, GIS post-processing steps, and accuracy assessment approach. Section 4 presents the outcomes of the stand delineation process, including spatial and thematic accuracy, and compares automated versus reference maps. Section 5 interprets the findings, compares them with previous studies, and highlights challenges in automation. Finally, Section 6 summarizes key findings, emphasizes the potential of semi-automated stand delineation, and outlines future research directions.

2. Materials

2.1. Study Area

This analysis focuses on the Talladega Division of the Talladega National Forest, which covers 95,271 ha of land in the northeastern part of the State of Alabama, USA (Figure 1). The climate of the region is humid and subtropical, where each year is characterized by mild winters and hot summers. The elevation of the landscape ranges from 160 to 735 m, and the average annual precipitation is about 1260 mm. Parts of the landscape are classified into three broad ecoregions (Valley, Piedmont, and Ridge). The dominant tree species include loblolly pine (*Pinus taeda* L.), shortleaf pine (*P. echinata* Mill.), longleaf pine (*P. palustris* Mill.), oak (*Quercus* spp.), yellow-poplar (*Liriodendron tulipifera* L.), red maple (*Acer rubrum* L.), hickory (*Carya* spp.), and many other minor deciduous species. Since the US national forest system began acquiring these lands in 1937, the management of stands of trees has involved both artificial regeneration and natural regeneration processes, the latter of which have been more prevalent in the last 40 years.

2.2. Data Sets

One dataset for the stand delineation process consists of county-level mosaiced orthophotographs developed by the National Agriculture Imagery Program (NAIP) of the U.S. Department of Agriculture, available at <https://datagateway.nrcs.usda.gov> (accessed on 10 April 2025). The images that form the basis for these orthophotographs were captured in 2021 using a large-format digital camera mounted inside a small aircraft. The range of reflected electromagnetic energy present in these images spans the true-color and near-infrared spectrum and is comprised of four spectral bands (red, green, blue, and near-infrared). These spectral bands enabled differentiation between various vegetation and land-cover types, based on unique spectral reflectance values in the visible and near-infrared regions. The spatial resolution of the county-level mosaiced orthophotographs is 0.3 m. For the purpose of this analysis, the spatial resolution of NAIP images was resampled to 5 m spatial resolution using the Resample function in ArcGIS Pro version 3.0 with the bilinear resampling technique. Developing stand boundaries with automated processes that are applied to GIS data with coarse spatial resolutions (>20 m) can result in unrealistic stand boundaries, as demonstrated in Figure 2. Therefore, the selection of a resampled 5 m spatial resolution was a trade-off between desired outcome accuracy and the volume of input data.

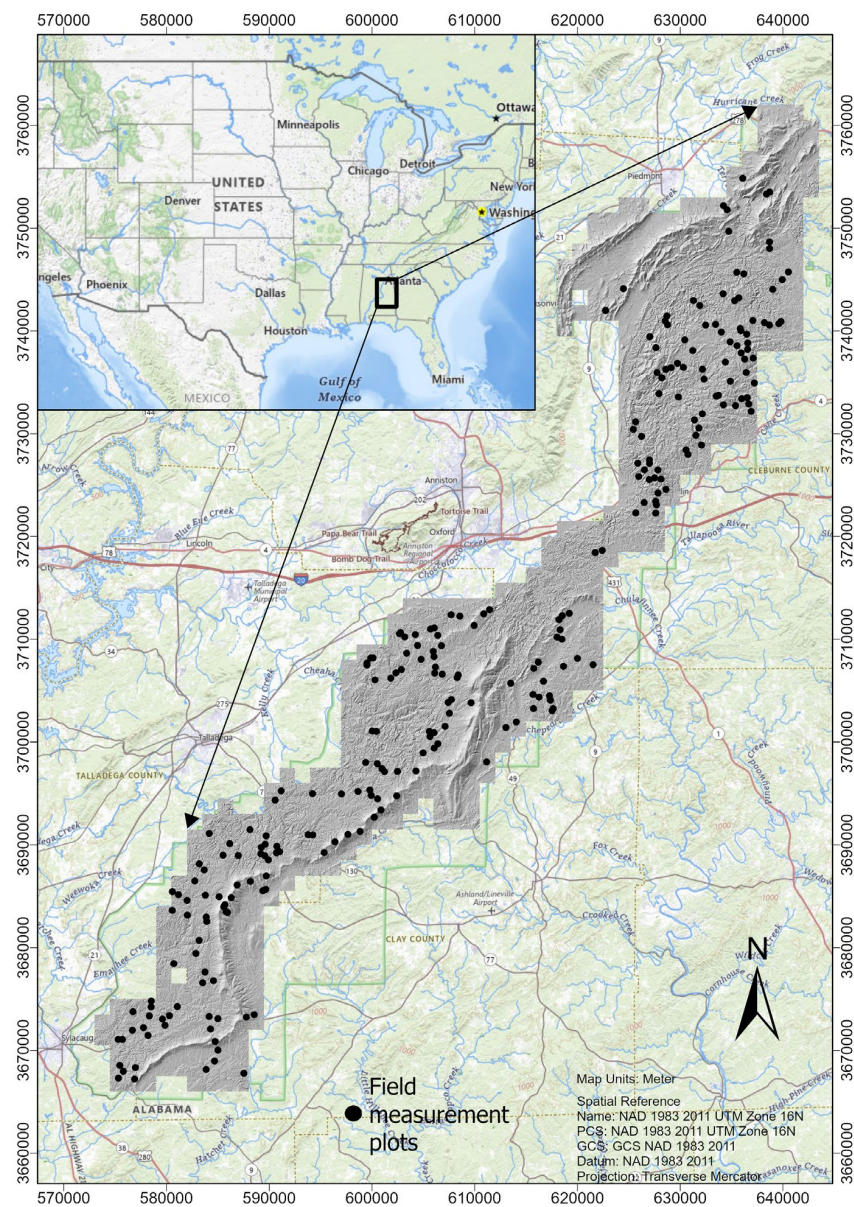


Figure 1. Hill shade map of the study area showing the locations of field measurement plots (Basemap source: Esri).

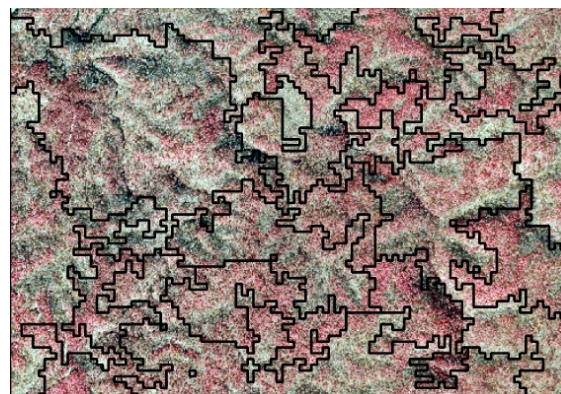


Figure 2. Unrealistic stand boundaries resulting from input data sets with a spatial resolution coarser than 20 m.

A LiDAR-derived digital terrain model (DTM) developed from a 2011 flight was also used in the stand delineation process. This model was created using a triangular irregular network algorithm with 5 m spatial resolution, which covered the entire study area. The reason for choosing a moderate spatial resolution was based on the relatively low point density of airborne LiDAR data (about 5 pts/m²) and pragmatic considerations, such as computation speed and space for data storage. Further, using the Talladega National Forest as a case study, Atkins et al. [17] showed that higher-resolution remote sensing data does not necessarily yield more accurate end products.

A landform index [18] GIS database was developed to represent a simple topographic measure as a proxy for the effect of landform on the distribution and composition of forest vegetation and for site productivity. The landform index was based on the average ground slope in eight directions. A ground slope map based on the DTM was used to create the landform map. While the original index values theoretically range from -1.0 to 1.0 , they were stretched to a range of 0 to 255 to better highlight differences across the landscape (Figure 3). Generally, higher values correspond to concave landforms, such as valleys and coves, whereas lower values often indicate convex features, such as ridges and saddles, depending on the slope gradient.

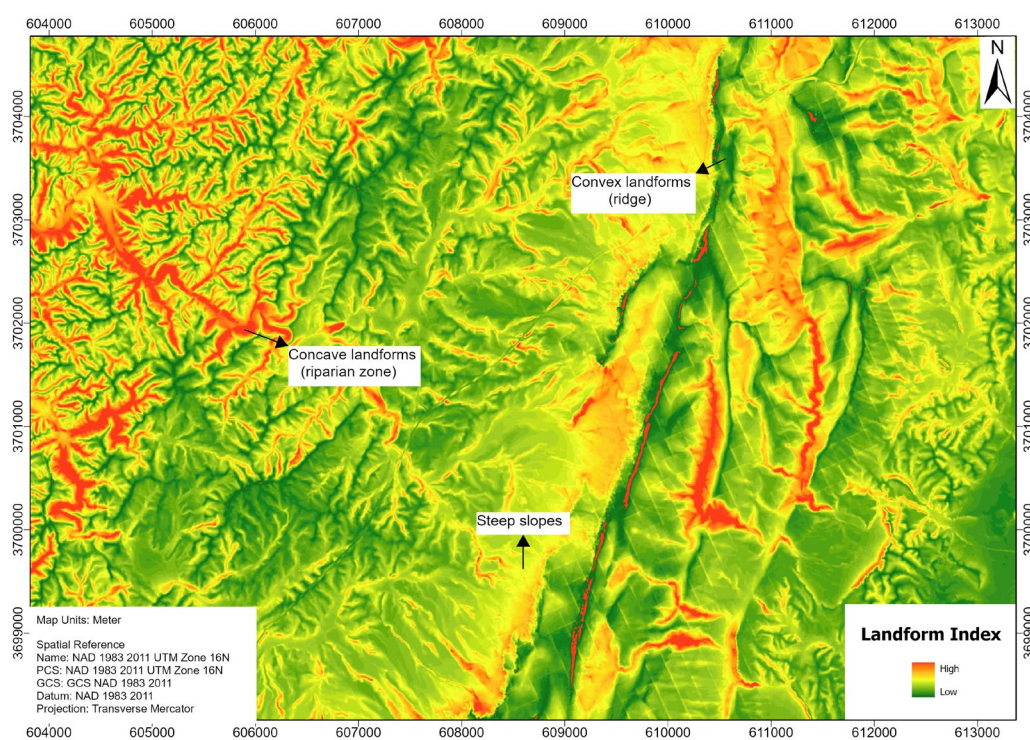


Figure 3. Landform index map for a portion of the study area. Higher values generally correspond to concave landforms, while lower values often indicate convex features. Median values (yellow pixels) represent areas with low to high slope gradients.

To act as reference datasets, a vector-based stand map was used to assess the spatial accuracy (stand boundaries) of the stand delineation results. This map was previously created by researchers at the University of Georgia through the visual interpretation of aerial photographs, along with several spatial data processing procedures to identify steep slope areas. This reference data covered 72% of the entire study area, as the researchers focused on actively managed areas within the Talladega National Forest. Additionally, inventory data collected from 255 circular, fixed-area (0.04 ha) field measurement plots were used to assess thematic accuracy (forest type) of the outcomes of the work. The pseudo-random distribution across operable lands within the study area was designed

for the purposes of another project [19] but provided valuable reference metrics for this analysis (Figure 1). All standing trees (>7.6 cm in diameter and >0.6 m in height) within the plots were measured, and their species were identified by cruise foresters.

3. Methods

The steps of the proposed methodology are presented in Figure 4. The following subsections provide a detailed description of each step.

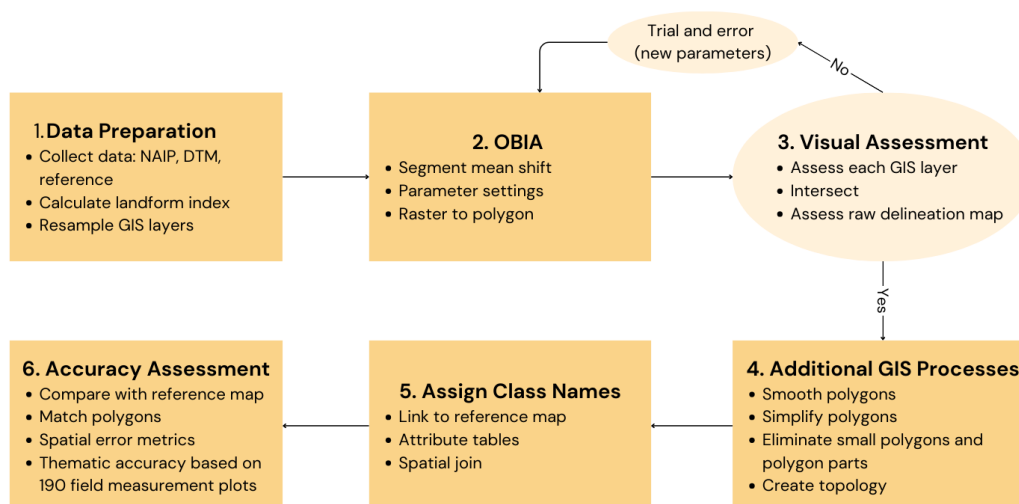


Figure 4. Overall workflow of the proposed method.

3.1. Object-Based Image Analysis (OBIA)

An OBIA process was employed to create the boundaries of forest stands. Among numerous OBIA algorithms described in the literature, the mean shift [20] was selected due to its practicality and availability as a segmentation tool in ArcGIS Pro [21]. The mean shift is a procedure-based image segmentation algorithm that serves as a natural extension of discontinuity-preserving smoothing algorithms. In this approach, each pixel is associated with a prominent mode of the joint domain density within its neighborhood, while nearby modes are filtered out using the generic feature space analysis technique [20]. Numerous studies have demonstrated the effectiveness of the mean shift algorithm [22,23]. In the present study, the NAIP images and landform index database were segmented individually because ArcGIS Pro did not allow more than one GIS database as input. Since the Talladega National Forest is relatively large, the algorithm required several hours to segment the entire area. Therefore, preliminary work focused on a smaller (5 km × 5 km) yet highly representative portion of the national forest (i.e., consisting of almost all land cover classes, Figure 5). In utilizing the *segment mean shift* algorithm, the following parameter assumptions were needed: spectral detail, spatial detail, and minimum segment size (in pixels). Spectral detail relates to the emphasis placed on the spectral differences of features in the imagery, while spatial detail emphasizes the spatial proximity of features in the imagery. Both parameters can be adjusted within a range of 1 to 20. Higher spectral detail values are suitable when distinguishing features with similar spectral characteristics, whereas higher spatial detail values are ideal for small, clustered features. Smaller spatial detail values typically produce smoother outputs. The minimum segment size, on the other hand, defines the minimum mapping unit and can be adjusted within a range of 1 and 9999. Segments smaller than the specified size are merged with their best-fitting neighboring segments [21].

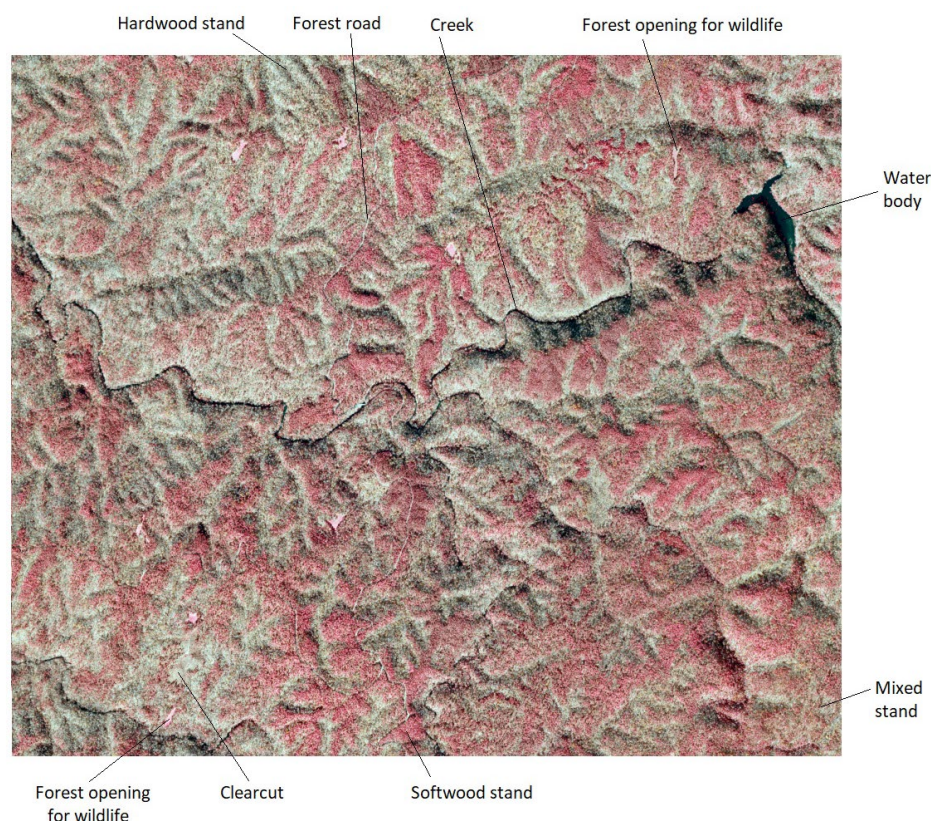


Figure 5. A representative color-infrared orthophotograph subsample of the Talladega National Forest exhibiting several land-cover types (Source: U.S. Department of Agriculture National Agricultural Imagery Program (NAIP)).

The segmentation tool was applied several times to the data using different sets of parameters to identify a reasonable set for each database that yielded visually adequate results. Then, the algorithm was applied across the entire study area using the best set of parameters. The algorithm generates raster GIS databases, which then need to be converted to vector GIS format using the *Raster to Polygon* function in ArcGIS Pro. After obtaining forest-wide stand delineation maps in vector format, the quality and consistency of the stand boundaries across the landscape were visually evaluated. Since the segmentation parameter sets were identified through trial and error based on the smaller, yet representative area of the national forest, special attention was paid to the assessment of outcome quality in different portions of the broader national forest. There seems to be no standard validation process for this type of work reported in the literature, as these processes are site- and data-specific [13,14].

3.2. Additional GIS Processes and Assignment of Class Names

Additional GIS processes were necessary to modify the stand delineation map in accordance with the following criteria suggested by U.S. Forest Service collaborators:

- The final GIS database should be vector-based, consisting of polygons (stands);
- The minimum mapping area of a stand should be 4 ha;
- Stand shapes should be smooth, as if delineated by a human analyst;
- Natural linear elements (i.e., creeks, roads, and ridges) in the landscape should serve as a foundation for stand boundaries (where possible);
- Forest characteristics (height, diameter, etc.) must be sufficiently homogeneous within stand polygons;

- Some forest areas are composed of “mixed stands” where different tree species are interspersed within the stand. The stands of this sort should not be divided into smaller patches based on individual trees;
- There are no gaps or overlaps among neighboring stands (topology must be established);
- Data format is shapefile (*.shp) compatible to analyze in GIS (Esri’s ArcGIS Pro is preferred).

One of the shape-related issues was prompted by the presence of overly detailed and zigzagged stand boundaries, particularly in the map created solely using NAIP imagery (Figure 6a). This was due to the relatively high spatial resolution and large variations in neighboring pixel values used in the OBIA process. Forest managers do not need to see individual tree-level detail in stand delineation maps. Therefore, this issue was addressed by applying the Polynomial Approximation with Exponential Kernel (PAEK) algorithm found in the *Smooth Polygon* function of ArcGIS Pro, using a 100 m tolerance. The resulting map initially seemed insufficiently generalized, so the same function was applied multiple times to produce the final result shown in Figure 6b. Another shape-related issue was the presence of polygons in complex geometrical features. For this, the *Simplify Polygon* function in ArcGIS Pro was employed using the Zhou-Jones algorithm [24] with a simplification tolerance of 100 m. The Zhou-Jones algorithm retains the weighted effective areas of polygons while generalizing complex boundaries, as shown in Figure 7.

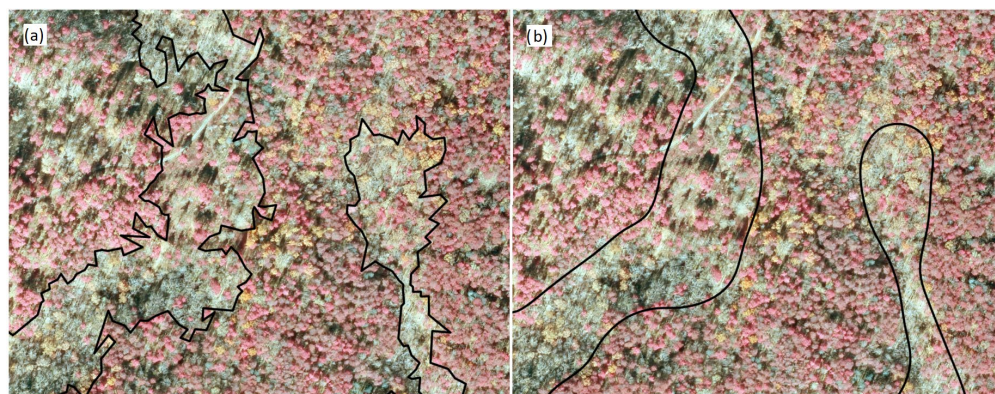


Figure 6. (a) Zig-zagged stand boundaries; (b) the same boundaries after the smoothing process in GIS.

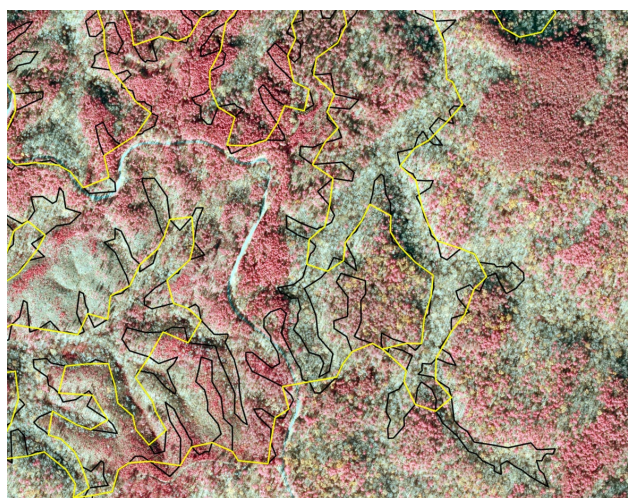


Figure 7. Polygon simplification process in GIS. The original OBIA-developed stand delineation is shown in black, while the simplified polygons are shown in yellow.

The size-related issue was associated with the operational reality that management of the case study forest area was based on relatively large areas rather than small, dispersed patches of land. To eliminate polygons smaller than 4 ha, the ArcGIS Pro Eliminate function was employed. Small polygons were subsequently merged with a neighboring polygon with the longest shared border. While this process removed unrealistically small polygons (slivers, no-data pixels), some meaningful areas (wildlife food plots, clearcuts, etc.) were also lost.

These processes were applied separately to the OBIA maps created from (a) the NAIP images and (b) the landform map. The two outcomes were then intersected to integrate the information from both. The geometry of the intersected database needed then to be repaired, and multipart polygons needed to be converted to single-part polygons using the *Multipart to Singlepart* function in ArcGIS Pro. The intersection of the two vector maps resulted in small polygons (<4 ha); thus, the *Eliminate* function was again employed with a 4 ha minimum size assumption. Very small holes in some polygons on the intersection map were then observed, perhaps due to image stitching areas on the orthophoto. To fill these holes, the *Eliminate Polygon Part* function was employed with an 'area' condition and a 1 ha size limit. Finally, topology was created to resolve overlapping polygon parts and other topological issues.

While the stand boundaries were visually adequate in the final delineation map, class names for the stands (i.e., tree species or species mixture) were lacking. To address this, the 'stand name' field in the attribute table of the reference map was joined to the polygons in the final stand delineation map using ArcGIS Pro's *Spatial Join* function. Specifically, the join operation used a one-to-one join along with the matching option of 'largest overlap'. Other options, such as 'intersect' and 'completely contain', did not work well in this case. This allowed the comparison of forest type designations between the reference map and the OBIA-generated stand map.

3.3. Accuracy Assessment

The spatial accuracy of the final stand delineation map was assessed by comparing it with 62 randomly selected polygons from the reference map. These polygons were a subset of the large reference map to make the accuracy assessment process efficient. The reference polygons were matched with their counterparts using the 'largest overlap' *Spatial Join* function option. Equations (1)–(3) were then applied to the polygon pairs:

$$OLO_{ij} = \text{area}(x_i \cap y_i) / \text{area}(y_i) \quad (1)$$

$$OLU_{ij} = \text{area}(x_i \cap y_i) / \text{area}(x_i) \quad (2)$$

$$\text{Overall agreement} = (OLO_{ij} + OLU_{ij}) / 2 \quad (3)$$

where OLO_{ij} is the fraction of overlapping area relative to the area of delineated object y_i in terms of over-segmentation; x_i is the corresponding reference object; and OLU_{ij} is the fraction of the overlapping area relative to the area of delineation object x_i in terms of under-segmentation. To find the intersected area ($\cap$) of x_i and y_i , a spatial intersect was employed. This approach is similar to that used by Ucar et al. [25] and Sanchez-Lopez et al. [1] for pairwise comparisons of polygons created by different devices or methods.

Thematic (classification) accuracy of the final map was also assessed based on tree species information retrieved from the collected inventory data plots. While the total number of plots was 255, 190 of them were used because of the limited overlap. The dominant tree species in each plot was compared against those found in the corresponding stand of the final delineation map. If the forest types matched, the classification was

considered correct, and vice versa. The overall thematic accuracy was then calculated using Equation (4):

$$\text{Overall agreement} = (\text{CCS}/\text{SS}) \times 100 \quad (4)$$

where CCS is the number of correctly classified stands, and SS is the total number of sample stands evaluated.

4. Results

The most visually adequate results were obtained using spectral and spatial detail parameters of 11 and 18 for the NAIP-based delineation map and 9 and 17 for the landform-based delineation map, respectively. The minimum segment size was set to 9999 for both delineation maps, which was the maximum value allowed by the algorithm and refers to the number of pixels in image objects (i.e., stand polygons). While the information in the NAIP imagery was helpful for discriminating tree species groups and forest biophysical structures (Figure 8a), the landform map proved useful for delineating riparian areas and other landscape elements (Figure 8b).

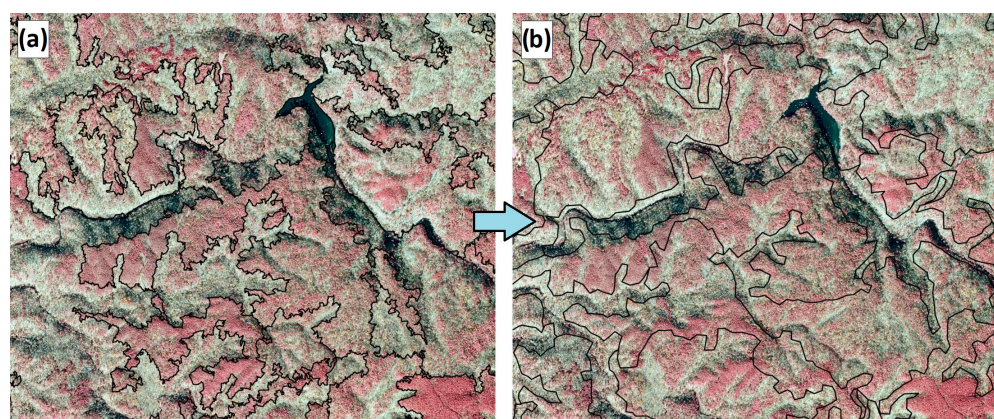


Figure 8. (a) Preliminary OBIA-developed stand boundaries delineated based on the U.S. Department of Agriculture National Agricultural Imagery Program (NAIP) imagery; and (b) the landform index map.

After intersecting the two delineation maps and applying additional GIS processes, the total number of polygons for the entire study area significantly decreased. General information on the final stand delineation map is provided in Table 1, alongside the reference map for comparison. Regarding spatial accuracy, the OLO_{ij} values ranged from 0.136 to 1.0, with an average of 0.679 (Table 2). The OLU_{ij} values for the same polygons ranged from 0.002 to 0.986, with an average of 0.182. Thus, the overall agreement was 0.430 when considering both over- and under-segmented polygons. This finding indicates a moderate spatial match (43%) between the stands of the final delineation map and the reference map. As for thematic (classification) accuracy, the dominant tree species in 108 out of 190 field measurement plots matched those recorded in the final delineation database attribute table. In contrast, in 82 out of 190 plots, the dominant tree species did not match those in the stand name field. Additionally, 65 out of 255 plots fell into stand polygons without a stand name due to the limited overlap between the final delineation and reference maps during the spatial join stage. Consequently, the overall agreement between the paired polygons was 56.8%, indicating that the thematic accuracy of the final stand delineation map was moderate and higher than the spatial accuracy rate. Examples of well- and poorly delineated portions of the study area can be found in Figures 9 and 10.

Table 1. Spatial characteristics of the stand map created in the present project compared to the reference stand map of the Talladega National Forest.

Spatial Characteristics	Final Stand Map	Reference Stand Map
The number of stands	2333	6922
Average stand size (ha)	40.8	13.7
Minimum stand size (ha)	4.0	0.1
Maximum stand size (ha)	2982.1	2433.0
Standard deviation (ha)	89.6	56.1
Total area covered (ha)	95,271.1	94,669.7

Table 2. Pairwise comparison of polygons from the final and reference stand maps.

No.	OLO _{ij}	OLU _{ij}	Overall Agreement	No.	OLO _{ij}	OLU _{ij}	Overall Agreement
1	0.548	0.182	0.365	32	0.582	0.032	0.307
2	0.566	0.036	0.301	33	1.000	0.033	0.517
3	0.562	0.361	0.461	34	0.646	0.053	0.349
4	0.529	0.093	0.311	35	0.646	0.042	0.344
5	0.244	0.047	0.146	36	1.000	0.002	0.501
6	0.992	0.204	0.598	37	0.561	0.055	0.308
7	0.982	0.044	0.513	38	0.744	0.504	0.624
8	0.989	0.137	0.563	39	0.881	0.074	0.478
9	1.000	0.039	0.519	40	0.644	0.068	0.356
10	0.536	0.208	0.372	41	0.766	0.062	0.414
11	0.982	0.105	0.544	42	0.701	0.106	0.404
12	0.983	0.064	0.524	43	0.501	0.166	0.334
13	0.456	0.051	0.254	44	0.789	0.550	0.669
14	0.477	0.289	0.383	45	0.719	0.047	0.383
15	0.434	0.058	0.246	46	0.879	0.128	0.503
16	0.645	0.150	0.397	47	0.361	0.470	0.415
17	0.573	0.173	0.373	48	0.797	0.264	0.530
18	0.470	0.637	0.553	49	0.434	0.986	0.710
19	0.666	0.202	0.434	50	0.680	0.070	0.375
20	0.986	0.197	0.592	51	0.988	0.270	0.629
21	0.366	0.433	0.400	52	0.691	0.055	0.373
22	0.676	0.184	0.430	53	0.637	0.178	0.407
23	0.948	0.111	0.530	54	0.696	0.100	0.398
24	0.940	0.292	0.616	55	0.883	0.585	0.734
25	0.461	0.048	0.255	56	0.703	0.018	0.360
26	0.781	0.510	0.646	57	0.519	0.122	0.320
27	0.580	0.065	0.323	58	0.688	0.277	0.482
28	1.000	0.048	0.524	59	0.682	0.146	0.414
29	0.357	0.134	0.245	60	0.685	0.092	0.388
30	0.806	0.150	0.478	61	0.250	0.150	0.200
31	0.136	0.307	0.222	62	0.664	0.006	0.335
Average					0.679	0.182	0.430

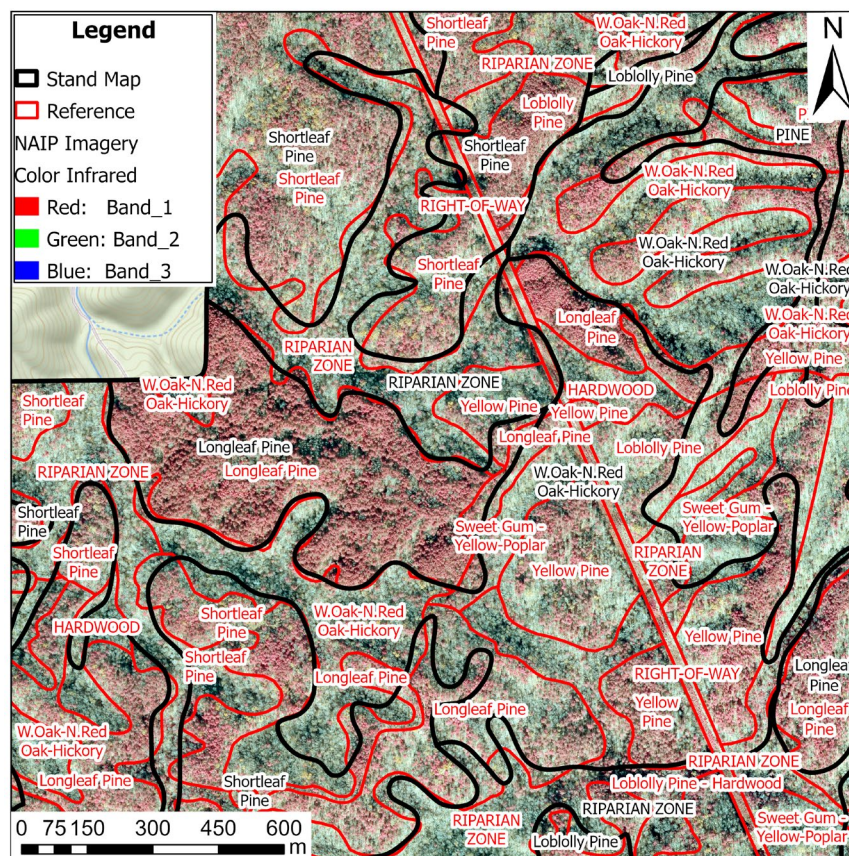


Figure 9. View from a portion where agreement between the OBIA-developed stand map and the reference map delineations is relatively good.

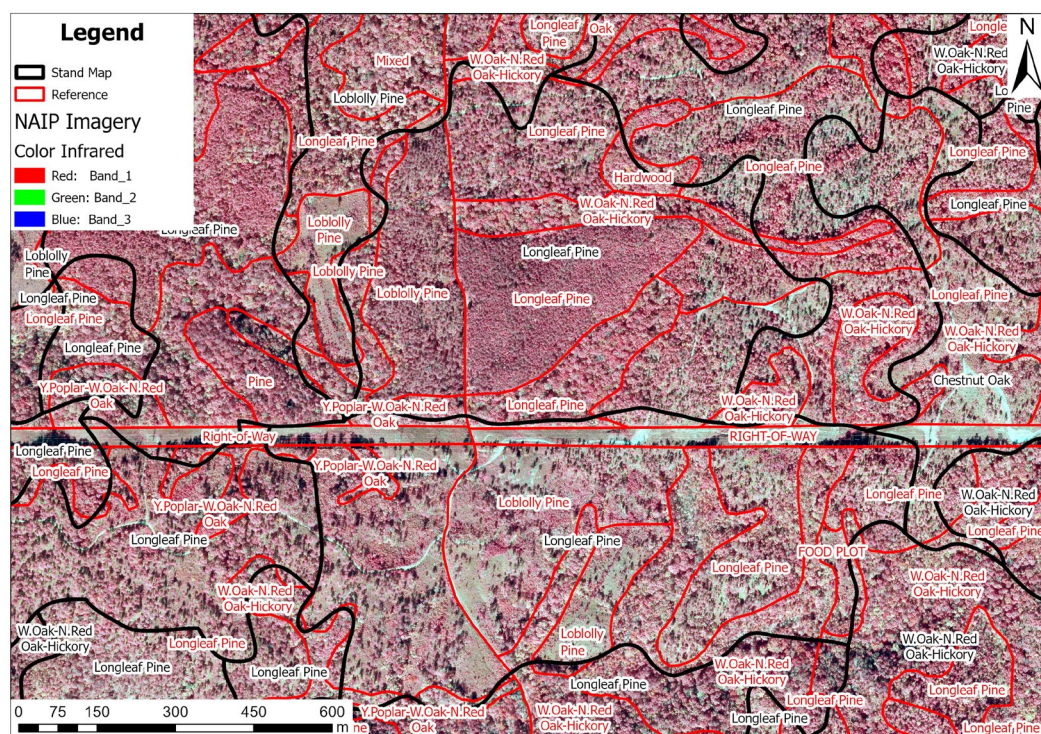


Figure 10. View from a portion where agreement between the OBIA-developed stand map and the reference map delineations is relatively poor.

5. Discussion

Within the last two decades, certain remote sensing products (e.g., airborne LiDAR and higher resolution aerial imagery, in particular) have become important resources for forest managers. The use of these products can be highly beneficial for forest management, as forest attributes can be characterized with relatively higher accuracy over broad landscapes [16,19,26,27]. GIS and remote sensing are, therefore, crucial fields associated with forest resource management, and digital databases, in their many formats and resolutions, provide opportunities to describe forests without the need for intensive field measurements. The selection of remote sensing products used in OBIA as input data is important; however, defining and selecting these products is challenging, as it can require experience with, and prior knowledge of, the area of interest [3,28]. Based on the evaluation, the most visually adequate stand delineation maps were created using composite color-infrared imagery (near-infrared, green, red) and landform index GIS databases. This may be because the visual interpretation also relied on aerial imagery and topographic features (e.g., creeks, ridges, sloped areas) of the landscape. While the information in color-infrared imagery helped discriminate tree species groups and forest structures, the landform index database was useful for delineating riparian areas and other landscape elements. Although a canopy height model derived from airborne LiDAR (collected in 2020–2021) was considered as one of the input data sets, it was not as useful for visually adequate stand delineation compared to the product obtained using NAIP color-infrared imagery and the landform database. Disregarding LiDAR-derived information in the segmentation process is a distinctive feature of the present study, as LiDAR metrics are increasingly commonly used in automated stand delineation research [3,4,29–31]. The resulting OBIA stand delineation showed a 43% spatial agreement when compared to the reference manually delineated stand map. While this rate is comparable to some previous work of this nature (e.g., Ozkan et al. [11], reporting 50% overall accuracy for their 14-class map; Pukkala et al. [3], with a mean R^2 of 55%–61%), the lower accuracy can be attributed to several factors. Firstly, the spatial accuracy assessment involved directly comparing individual polygons (stands) based on the precise locations of their segment borders. Recent studies indicate that reference stand maps, manually and subjectively created through visual interpretation of optical imagery, may not always be reliable. For instance, Pukkala et al. [3] analyzed Spain's official forest map, developed via visual interpretation, and compared it to their automated stand delineation map. Their analysis revealed that the automated segments explained a greater proportion of variance for selected LiDAR metrics and growing stock variables than the official map. This result suggests that automated stand delineation, though less visually appealing over optical imagery, might result in a closer representation in terms of internal consistency (i.e., within-stand homogeneity) and external variability (i.e., between-stand heterogeneity) when forest inventory measures (e.g., basal area, volume, canopy height, stand age) are considered.

The second factor that potentially reduced the spatial and thematic accuracy of the stand delineation map was the challenging (in terms of management) topography, large area coverage, and structurally complex forest characteristics of the study area. Since the forests within the study area are mostly natural in origin, including still vast portions of unmanaged lands (e.g., wilderness, viewsheds), the forest exhibits a highly heterogeneous structure in terms of composition (e.g., multi-species stands) and configuration (e.g., diverse age classes, multi-layered stands). According to the ground inventory, it was not uncommon to find more than 10 tree species in the “white oak-northern red oak-hickory” mixed stand type, including maple, yellow-poplar, sweetgum (*Liquidambar styraciflua* L.), sourwood (*Oxydendrum arboreum* (L.) DC.), and other oak species. Such diversity, among other factors, makes the OBIA process more challenging due to the segmentation of small patches.

When the segment size parameter was set to a higher value, some important features, such as wildlife food plots, groups of retention trees, and recent clearcuts, were omitted. This resulted in a greater emphasis on post-processing efforts in the GIS environment. Handling an area of the case study's size also proved difficult. An orthomosaic composed of hundreds of very-high-resolution scenes collected over such a vast landscape may result in radiometric differences in pixel reflectance, even within the same stand that spans more than one scene. Subedi et al. [16] also noted that such issues with the NAIP orthomosaics are common in projects involving large areas and often stem from different imagery acquisition times.

Third, while the manually delineated stand database used as a reference acted as a basis for comparison of the OBIA-developed map, the manually delineated reference stand map was not perfect. After it was produced nearly a decade ago through subjective aerial image interpretation processes supplemented by LiDAR characteristics of the landscape, the reference map itself did not undergo a validation process; it simply was viewed as a much better representation of the forest stand boundaries within the case study than the previous resource. Therefore, one should bear in mind that, as with nearly all GIS databases developed using digitizing and editing processes within GIS software, some error (spatial location, systematic, blunder) should be expected even though the intent is to capture and describe a system of interest to the best ability of the practitioners. Therefore, the lower accuracy of the OBIA-developed stand map should be tempered a bit to recognize that the reference map was not perfect.

Lastly, some of the criteria specified by forest managers may have limited the final accuracy in this study. For instance, stand polygons smaller than 4 ha were considered undesirable. To adhere to this requirement, several generalization and elimination algorithms were applied during the post-processing stage, which may have resulted in the loss of meaningful information in the final output. While such requirements are inevitable and often useful for practical forest management, they may conflict with certain aspects of accuracy assessment in remote sensing. Therefore, future research should aim to strike a balance between the operational needs of forest management planning and the precision efforts in remote sensing and GIS projects.

6. Conclusions

An automated process for creating a forest stand map in a highly heterogeneous and structurally complex case study area was described in this work. The object-based image analysis (OBIA) method was first applied to aerial imagery and then applied to a landform index database. These two products were smoothed and simplified to reduce some of the noise produced through the OBIA process. These two products were then combined to capitalize on the information provided by potential stand delineations as viewed in the aerial imagery and by potential stand delineations as viewed by the topography of the landscape. Afterwards, some simplification and smoothing processes were again applied to arrive at the final product. Even though the pseudo-automated process had the intent of emulating the delineation of forest stand boundaries by human practitioners, correspondence with a digitized, yet subjective, forest stand boundary map created through imagery interpretation processes was low to moderate.

Further work in this area is suggested to better align artificial intelligence (AI) with the task of stand boundary delineation often pursued by forest managers. Supervised and unsupervised AI methods could be employed to optimize segmentation parameters and GIS post-processing procedures. By leveraging AI-driven approaches, the applicability of the proposed methodological pipeline could be expanded beyond the current case study, making it more adaptable to diverse forest ecosystems and management needs.

Author Contributions: Conceptualization, P.B., J.S. and C.V.; methodology, T.L., P.B. and C.V.; software, T.L. and C.V.; validation, P.B. and C.V.; formal analysis, C.V.; data curation, K.M., P.B., T.L. and J.S.; writing—original draft preparation, C.V.; writing—review and editing, P.B., K.M., J.S., T.L. and C.V.; visualization, C.V.; supervision, P.B. and J.S.; project administration, P.B.; funding acquisition, P.B. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the U.S. Department of Agriculture, Forest Service, Southern Region, Federal Grant Number 22-CS-11080100-232 (Talladega Division LiDAR Project). This work was also supported by the U.S. Department of Agriculture, National Institute of Food and Agriculture, Sustainable Agricultural Systems program, PERSEUS grant, #2023-68012-38992. The findings and conclusions in this work have not been formally disseminated by the U.S. Department of Agriculture and should not be construed to represent any agency determination or policy. The U.S. government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Sanchez-Lopez, N.; Boschetti, L.; Hudak, A.T. Semi-automated delineation of stands in an even-age dominated forest: A LiDAR-GEOBIA two-stage evaluation strategy. *Remote Sens.* **2018**, *10*, 1622. [\[CrossRef\]](#)
2. Demirpolat, C.; Leloglu, U.M. Forest stand segmentation with multi-temporal Sentinel-2 imagery and superpixels. *J. Appl. Remote Sens.* **2024**, *18*, 014530. [\[CrossRef\]](#)
3. Pukkala, T.; Aquilué, N.; Kutchartt, E.; Trasobares, A. A hybrid method for delineating homogeneous forest segments from LiDAR data in Catalonia (Spain). *Eur. J. Remote Sens.* **2024**, *57*, 2425337. [\[CrossRef\]](#)
4. Xiong, H.; Pang, Y.; Jia, W.; Bai, Y. Forest stand delineation using airborne LiDAR and hyperspectral data. *Silva Fenn.* **2024**, *58*, 23014. [\[CrossRef\]](#)
5. Hernando, A.; Tiede, D.; Albrecht, F.; Lang, S. Spatial and thematic assessment of object-based forest stand delineation using an OFA-matrix. *Int. J. Appl. Earth Obs. Geoinf.* **2012**, *19*, 214–225. [\[CrossRef\]](#)
6. Kadiogullari, A.İ.; Sayin, M.A.; Çelik, D.A.; Borucu, S.; Çil, B.; Bulut, S. Analysing land cover changes for understanding of forest dynamics using temporal forest management plans. *Environ. Monit. Assess.* **2014**, *186*, 2089–2110. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Başkent, E.Z.; Köse, S.; Keleş, S. The forest management planning system of Turkey: Constructive criticism towards the sustainable management of forest ecosystems. *Int. For. Rev.* **2005**, *7*, 208–217. [\[CrossRef\]](#)
8. GDF. *Ecosystem-Based Multifunctional Forest Planning Guidelines* (Code No: 299); The Turkish General Directorate of Forestry: Ankara, Turkey, 2017. (In Turkish)
9. Öztürk, M.G.; Bekar, İ.; Tavşanoğlu, Ç. Rethinking lightning-induced fires: Spatial variability and implications for management policies. *For. Ecol. Manag.* **2024**, *572*, 122262. [\[CrossRef\]](#)
10. Bilgili, E.; Küçük, Ö.; Sağlam, B.; Coşkun, K.A. Büyük Orman Yangınları: Sebepleri, Organizasyonu ve İdaresi. In *Orman Yangınları: Sebepleri, Etkileri, İzlenmesi, Alınması Gereken Önlemler ve Rehabilitasyon Faaliyetleri*; Kavzoğlu, T., Ed.; TÜBA, Ankara Basım Yayın Hizmetleri: Ankara, Turkey, 2021; pp. 1–23. (In Turkish)
11. Ozkan, U.Y.; Demirel, T.; Ozdemir, I.; Sağlam, S.; Mert, A. Examining LiDAR–WorldView-3 data synergy to generate a detailed stand map in a mixed forest in the north-west of Turkey. *Adv. Space Res.* **2020**, *65*, 2608–2621. [\[CrossRef\]](#)
12. Blaschke, T.; Lang, S.; Hay, G.J. *Object-Based Image Analysis—Spatial Concepts for Knowledge-Driven Remote Sensing Application*; Springer: Berlin/Heidelberg, Germany, 2008; p. 817.
13. Yurtseven, H.; Akgul, M.; Coban, S.; Gulci, S. Determination and accuracy analysis of individual tree crown parameters using UAV based imagery and OBIA techniques. *Measurement* **2019**, *145*, 651–664. [\[CrossRef\]](#)
14. Kim, M.; Madden, M.; Warner, T. Estimation of optimal image object size for the segmentation of forest stands with multispectral IKONOS imagery. In *Object-Based Image Analysis (Spatial Concepts for Knowledge-Driven Remote Sensing Applications)*; Springer: Berlin, Germany, 2008; pp. 291–307.
15. Costa, H.; Foody, G.M.; Boyd, D.S. Supervised methods of image segmentation accuracy assessment in land cover mapping. *Remote Sens. Environ.* **2018**, *205*, 338–351. [\[CrossRef\]](#)
16. Subedi, M.R.; Portillo-Quintero, C.; Kahl, S.S.; McIntyre, N.E.; Cox, R.D.; Perry, G. Leveraging NAIP imagery for accurate large-area land use/land cover mapping: A case study in central Texas. *Photogramm. Eng. Remote Sens.* **2023**, *89*, 547–560. [\[CrossRef\]](#)

17. Atkins, J.W.; Costanza, J.; Dahlin, K.M.; Dannenberg, M.P.; Elmore, A.J.; Fitzpatrick, M.C.; Hakkenberg, C.R.; Hardiman, B.S.; Kamoske, A.; LaRue, E.A.; et al. Scale dependency of lidar-derived forest structural diversity. *Methods Ecol. Evol.* **2023**, *14*, 708–723. [[CrossRef](#)]
18. McNab, W.H. A topographic index to quantify the effect of mesoscale landform on site productivity. *Can. J. For. Res.* **1993**, *23*, 1100–1107. [[CrossRef](#)]
19. Lee, T.; Vatandaslar, C.; Merry, K.; Bettinger, P.; Peduzzi, A.; Stober, J. Estimating forest inventory information for the Talladega National Forest using airborne laser scanning systems. *Remote Sens.* **2024**, *16*, 2933. [[CrossRef](#)]
20. Comaniciu, D.; Meer, P. Mean shift: A robust approach toward feature space analysis. *IEEE Trans. Pattern Anal. Mach. Intell.* **2002**, *24*, 603–619. [[CrossRef](#)]
21. ArcGIS, version Pro 3.0; Environmental Systems Research Institute Inc.: Redlands, CA, USA, 2022.
22. Hamal, M.; Shah Nawaz, P. Comparison of the direct supervised classification and segment mean shift classification: A case study of Hetauda sub-metropolitan city of Nepal. *J. Geoinf. Nepal* **2024**, *23*, 35–47. [[CrossRef](#)]
23. Zaforemska, A.; Xiao, W.; Gaulton, R. Individual tree detection from UAV lidar data in a mixed species woodland. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2019**, *42*, 657–663. [[CrossRef](#)]
24. Zhou, S.; Jones, C.B. Shape-aware line generalization with weighted effective area. In *Developments in Spatial Data Handling*; Fisher, P.F., Ed.; Springer: Berlin/Heidelberg, Germany, 2005; pp. 369–380. [[CrossRef](#)]
25. Ucar, Z.; Bettinger, P.; Weaver, S.; Merry, K.L.; Faw, K. Dynamic accuracy of recreation-grade GPS receivers in oak-hickory forests. *Forestry* **2014**, *87*, 504–511. [[CrossRef](#)]
26. Fassnacht, F.E.; White, J.C.; Wulder, M.A.; Næsset, E. Remote sensing in forestry: Current challenges, considerations and directions. *Forestry* **2024**, *97*, 11–37. [[CrossRef](#)]
27. Goodbody, T.R.H.; Coops, N.C.; Irwin, L.A.K.; Armour, C.C.; Saunders, S.C.; Dykstra, P.; Butson, C.; Perkins, G.C. Integration of Airborne Laser Scanning data into forest ecosystem management in Canada: Current status and future directions. *For. Chron.* **2024**, *100*, 238–258. [[CrossRef](#)]
28. Silveyra Gonzalez, R.; Lafiti, H.; Weinacker, H.; Dees, M.; Koch, B.; Heurich, M. Integrating LiDAR and high-resolution imagery for object-based mapping of forest habitats in a heterogeneous temperate forest landscape. *Int. J. Remote Sens.* **2018**, *39*, 8859–8884. [[CrossRef](#)]
29. Dechesne, C.; Mallet, C.; Le Bris, A.; Gouet, V.; Hervieu, A. Forest stand segmentation using airborne lidar data and very high resolution multispectral imagery. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2016**, *41*, 207–214. [[CrossRef](#)]
30. Varo-Martínez, M.A.; Navarro-Cerrillo, R.M.; Hernández-Clemente, R.; Duque-Lazo, J. Semi-automated stand delineation in Mediterranean *Pinus sylvestris* plantations through segmentation of LiDAR data: The influence of pulse density. *Int. J. Appl. Earth Obs. Geoinf.* **2017**, *56*, 54–64. [[CrossRef](#)]
31. Sun, Y.; Wang, W.; Pukkala, T.; Jin, X. Stand delineation based on laser scanning data and simulated annealing. *Eur. J. For. Res.* **2021**, *140*, 1065–1080. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.