

Article

Improving the Individual Tree Parameters Estimation of a Complex Mixed Conifer—Broadleaf Forest Using a Combination of Structural, Textural, and Spectral Metrics Derived from Unmanned Aerial Vehicle RGB and Multispectral Imagery

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Abstract: Individual tree parameters are essential for forestry decision-making, supporting economic valuation, harvesting, and silvicultural operations. While extensive research exists on uniform and simply structured forests, studies addressing complex, dense, and mixed forests with highly overlapping, clustered, and multiple tree crowns remain limited. This study bridges this gap by combining structural, textural, and spectral metrics derived from unmanned aerial vehicle (UAV) Red–Green–Blue (RGB) and multispectral (MS) imagery to estimate individual tree parameters using a random forest regression model in a complex mixed conifer–broadleaf forest. Data from 255 individual trees (115 conifers, 67 Japanese oak, and 73 other broadleaf species (OBL)) were analyzed. High-resolution UAV orthomosaic enabled effective tree crown delineation and canopy height models. Combining structural, textural, and spectral metrics improved the accuracy of tree height, diameter at breast height, stem volume, basal area, and carbon stock estimates. Conifers showed high accuracy ($R^2 = 0.70$ – 0.89) for all individual parameters, with a high estimate of tree height ($R^2 = 0.89$, RMSE = 0.85 m). The accuracy of oak ($R^2 = 0.11$ – 0.49) and OBL ($R^2 = 0.38$ – 0.57) was improved, with OBL species achieving relatively high accuracy for basal area ($R^2 = 0.57$, RMSE = $0.08 \text{ m}^2 \text{ tree}^{-1}$) and volume ($R^2 = 0.51$, RMSE = $0.27 \text{ m}^3 \text{ tree}^{-1}$). These findings highlight the potential of UAV metrics in accurately estimating individual tree parameters in a complex mixed conifer–broadleaf forest.

Keywords: tree parameters; UAV metrics; structure from motion; UAV photogrammetry; hemi-boreal forest; random forest model



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1. Introduction

Individual tree parameters, such as tree height (H), diameter at breast height (DBH), basal area (BA), stem volume (V), and carbon stock (CST), are crucial for accurate forest inventories and sustainable forest management [1]. These parameters hold significant economic and ecological value, supporting the single-tree management of high-value timber species in mixed conifer–broadleaf forests [2–4]. Monitoring individual trees enables the assessment of tree growth and structure, biomass accumulation, and biodiversity conservation, while contributing to climate change mitigation and timber resource optimization [1,5,6]. Accurate estimation of individual tree parameters also facilitates forest

health monitoring by enabling early detection of tree-level stress indicators, such as reductions in H or BA growth, which can signal potential threats like pests, diseases, or environmental stressors. Such insights are essential for timely interventions and risk mitigations [7–9]. Additionally, precise individual parameter estimation supports adaptive management practices, such as selective thinning or regeneration planning, ensuring the long-term health, resilience, and sustainability of forest landscapes [1,8,10,11]. Therefore, individual tree parameter estimations play a pivotal role in promoting sustainable forest landscapes and informed decision-making processes [12,13].

Forest inventory using conventional methods are time-consuming, labor-intensive, inefficient, and often impractical in inaccessible areas [14,15]. Remote sensing (RS) technology offers a more efficient alternative, enabling precise estimation of individual tree parameters in mixed conifer–broadleaf forests. Advances in RS provide high-resolution forestry data and robust methodologies [1,16], improving the accuracy of monitoring individual tree growth and spatial distribution on a large scale [11,17–19].

While satellite imagery has been widely used to estimate forest structural parameters, its application for individual tree parameters is limited by low spatial resolution and atmospheric interference [20–22]. Among RS technologies, unmanned aerial vehicle (UAV) photogrammetry and light detection and ranging (LiDAR) are frequently used to obtain 3D forest information [17,23]. LiDAR is an active RS technology; emits laser beams to detect objects; and is highly effective for capturing structural details at both forest and individual tree scales, including tree height, crown dimensions, and biomass [17,22,23]. However, LiDAR sensors lack spectral information, which is critical for continuous monitoring [24,25]. To address this limitation, spectral sensors can be mounted alongside LiDAR on UAV platforms, enabling the simultaneous collection of structural and spectral data.

UAV photogrammetry is a specialized method created for 3D mapping in the RS field, and it has rapidly advanced in recent years [26,27]. Studies have shown that its accuracy in estimating individual tree parameters is comparable to that of LiDAR [28,29], with additional advantages such as low cost, repeatability, and high flexibility [23]. Structure from Motion (SfM) in UAV photogrammetry efficiently converts 2D digital aerial photographs into 3D photogrammetric point clouds [26], enabling detailed forest canopy characterization and visualization of individual tree canopies [1,30]. In dense, clustered, and highly overlapping canopy forests, UAV photogrammetry excels at identifying tree canopy edges and accurately delineating tree crowns, using rich textural features [1,31]. High-resolution imagery also reduces the likelihood of missing treetops in complex forests [30]. Moreover, UAV platforms support various sensors, enabling the collection of spectral information from Red–Blue–Green (RGB), multispectral (MS), and hyperspectral imagery [28,32], serving as an affordable supplementary data source.

Advancements in UAV photogrammetry have enabled accurate prediction of individual tree parameters in simple-structured, even-aged, sparse forests. However, challenges persist in dense, clustered, complex, mixed, and highly overlapped forests due to missing crown information [12,14,33]. Moe et al. [4] reported a correlation of 0.68 for H accuracy between field measurement and UAV RGB photogrammetry in a mixed conifer–broadleaf forest with high-valued timber species. Accuracy varied across the species: castor aralia had the highest H accuracy ($R^2 = 0.77$, RMSE = 2.04 m), followed by monarch birch ($R^2 = 0.27$, RMSE = 1.77 m) and oak ($R^2 = 0.10$, RMSE = 1.96 m). For tree DBH, correlations between field and UAV photogrammetry were 0.72, 0.57, and 0.75 for the abovementioned species, respectively. These studies employed manual crown delineation and multiresolution segmentation for individual tree parameter estimation. Data fusion approaches using LiDAR and optical sensors for biomass ($R^2 = 0.33$ – 0.82) and volume ($R^2 = 0.39$ – 0.87) estimation have shown a wide range of accuracy [25]. Zhao et al. [11] achieved high accuracy for H in

coniferous forests ($R^2 = 0.87$, RMSE = 0.21 m), followed by mixed conifer–broadleaf forest ($R^2 = 0.84$, RMSE = 0.37 m) and broadleaf forests ($R^2 = 0.84$, RMSE = 0.44 m), using LiDAR data. However, studies on estimating individual tree parameters in complex, dense, and mixed forests using UAV photogrammetry remain limited.

Structural, spectral, and textural metrics derived from point clouds and imagery have been used to estimate individual tree parameters [28,34,35]. Combining UAV remote-sensing variables such as structural, textural, and spectral metrics generally improves accuracy in estimating forest structural parameters using UAV RGB imagery [18]. Textural information is particularly important for capturing spatial details of forest structural arrangements [18,34]. In a previous study [28], we estimated the forest structural parameters at stand level using a combination of these metrics derived from UAV RGB imagery in mixed conifer–broadleaf forests. The results showed that combining these metrics enhanced the estimation accuracy of H, DBH, BA, V, and CST using a random forest (RF) model. However, using this for estimating individual tree parameters in mixed conifer–broadleaf forests is limited. Spectral metrics from MS imagery have been used for tree species classification [11,19,36,37], but their use for estimating individual tree parameters in mixed forests is underexplored. Moreover, most studies focus on H and DBH, with limited exploration of tree BA, V, and CST in complex forests. While area-based forest structural parameters provide high accuracy [28], accurately predicting individual tree parameters in complex mixed conifer–broadleaf forests remains challenging. This study extends previous work by estimating the same parameters (H, DBH, BA, V, and CST) at the individual tree level using a combination of structural, textural, and spectral metrics from both UAV RGB and MS imagery in mixed conifer–broadleaf forests. The key difference is the scale of parameter analysis at the individual tree level, along with the integration of MS imagery.

Given the challenges in predicting individual tree parameters in mixed conifer–broadleaf forests, we aimed to combine UAV metrics, comprising structural, textural, and spectral metrics. Structural and textural metrics were extracted from the canopy height model (CHM), while spectral metrics were derived from RGB and MS imagery. An RF model was used to estimate individual tree parameters. The research questions guiding this study are as follows: (1) Can high-resolution UAV orthomosaic enable the accurate delineation of individual tree crowns and CHM generation in mixed conifer–broadleaf forest? (2) Which UAV metrics are most important for predicting individual tree parameters in this forest? (3) Can UAV photogrammetry improve the estimation accuracy of H, DBH, BA, V, and CST for conifer, oak and other broadleaf (OBL) species by combining UAV metrics from UAV RGB and MS imagery? Our approach significantly aids forestry practitioners in estimating individual tree parameters in complex mixed conifer–broadleaf forests. The application of high-resolution UAV imagery assists in delineating individual tree species. By integrating UAV-derived metrics from RGB and multispectral (MS) imagery, we provide accurate individual tree parameters that support forest inventory efforts. Traditional ground surveys are time-consuming and labor-intensive, making frequent data collection impractical. In contrast, our approach enables data collection at any time using UAV photogrammetry, reducing the burden of conventional surveys. This integrated method highlights the importance of individual tree parameter estimation, particularly in complex forest environments.

2. Materials and Methods

2.1. Study Site

This study was carried out at the University of Tokyo Hokkaido Forest (UTHF), located at 43°10–20′ N, 142°18–40′ E, and 190–1459 m asl, in Furano City in Hokkaido, Northern Japan (Figure 1). UTHF is an uneven-aged, hemiboreal, and mixed conifer–

broadleaf forest situated between temperate deciduous and boreal evergreen coniferous forests, encompassing an area of 22,708 ha. Dominant conifer species include *Abies sachalinensis* (Todo fir), *P. glehnii* (red spruce), and *Picea jezoensis* (Yezo spruce), while dominant broadleaf species are *Quercus crispula* (oak), *Betula maximowicziana* (Monarch birch), *Kalopanax septemlobus* (castor aralia), *Acer pictum* (Painted maple), *Tilia japonica* (linden), *Fraxinus mandshurica* (Manchurian ash), and *Taxus cuspidata*. Dwarf bamboo species, *Sasa kurilensis* and *S. senanensis*, cover the forest floor. From 2001 to 2008, the arboretum's average annual temperature was 6.4 °C, with annual rainfall totaling 1297 mm at the elevation of 230 m asl. The forest floor is snow-covered from November to April, with snow accumulation reaching up to 1 m [2,28]. The study site, forest sub-compartment 68 E, was selected due to its high distribution of oak, high-valued timber species, particularly for whisky barrel production. Conifers, oak, and other broadleaf (OBL) species were categorized for the study. The study area spans 31 ha, with elevations ranging from 425 m to 500 m asl [38]. The study site has a mean tree density of 562 stems ha⁻¹ (DBH ≥ 5 cm, standard deviation = 73 stems ha⁻¹, range = 460–656 stems ha⁻¹) based on five inventory plots, each with a dimension of 50 m × 50 m (source: UTHF 2020 inventory data, March).

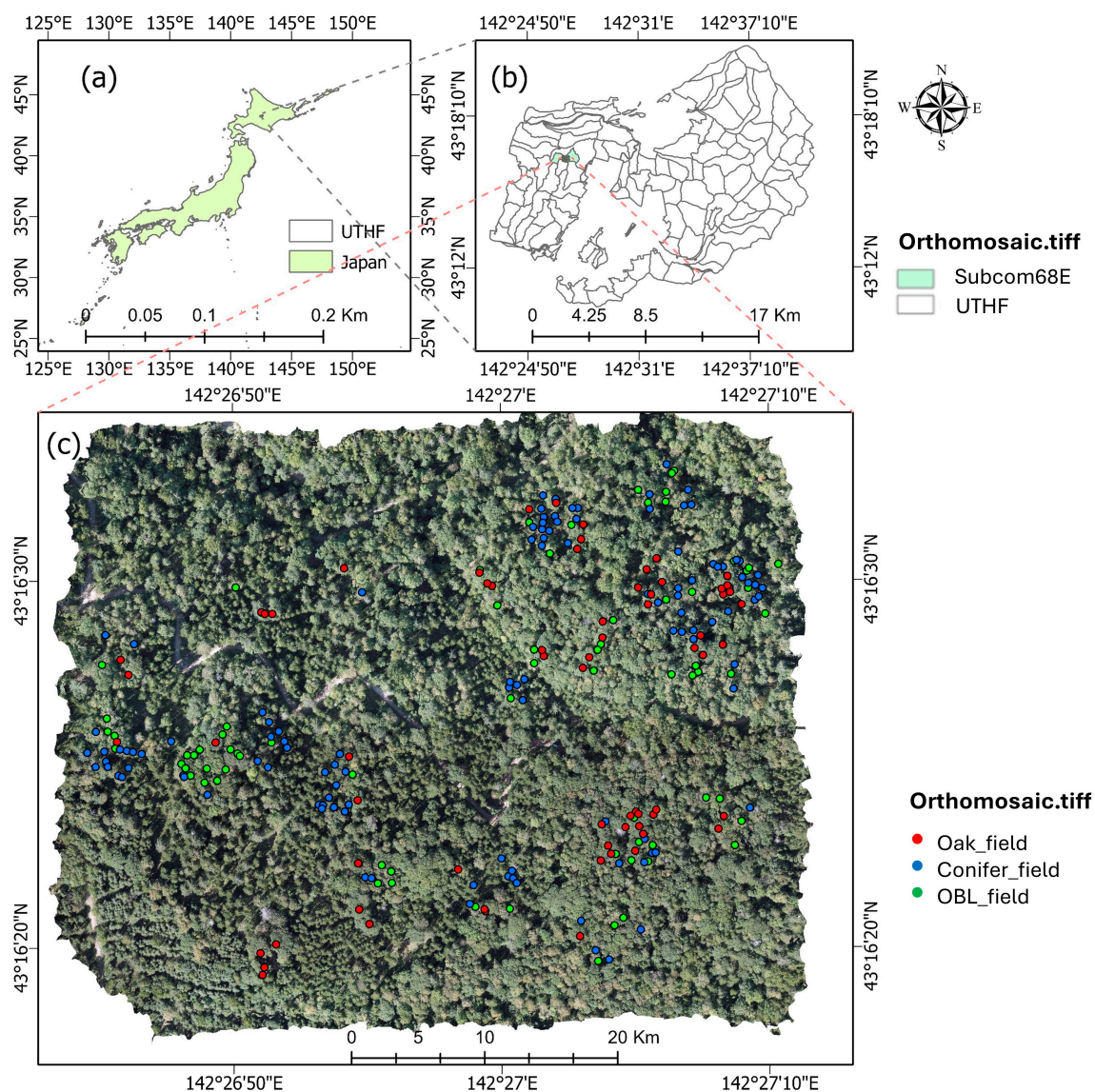


Figure 1. Study area map: (a) location of the UTHF in Japan; (b) sub-compartment 68 E in the UTHF; and (c) spatial tree location of oak, conifer, and other broadleaf (OBL) species in the UAV orthomosaic.

2.2. Collection of Field Data

A field survey was conducted in February 2023 to measure tree geospatial positions, H, and DBH. To identify the spatial position of dominant trees (≥ 24 m) prior to the field survey, we used a freely available web application by Silva et al. [39] (<https://carlosasilva.shinyapps.io/weblidar-treetop/>, accessed on 15 January 2023) which reduced field work time. Trees were randomly selected across the study area (Figure 1c). Geospatial positions of trees were recorded using a real-time kinematic (RTK) system of global navigation satellite system (GNSS) with a dual-frequency receiver (DG-PRO1RWS, BizStation Corp., Matsumoto City, Japan). In total, 255 trees were identified, comprising 115 conifers, 67 Japanese oak, and 73 OBL species. DBH was measured with a diameter tape at 1.3 m from the ground floor, and BA was calculated based on DBH. H measurements focused on conifers, as broadleaf trees had shed their leaves during the survey, improving the visibility of conifer treetops. H was measured three times, using a Vertex III hypsometer (Haglöf Sweden AB, Långsele, Sweden), and the average value was recorded. For the conifer H prediction, only 52 field-measured trees were used, while 115 trees were utilized for other individual tree parameters. H measurements for oak and OBL were not conducted due to overlapping canopies and multiple tree crowns, which are characteristic of complex forests. Instead, H for these species was estimated using a H-DBH model, a widely adopted method H prediction [40–42]. A nonlinear regression model (Equation (1)) was applied to derive the H-DBH relationship [42,43], based on measurements from 216 trees (oak and OBL) in other forest compartments (16, 65–66, and 03) recorded during the UTHF 2023 field survey.

$$H = 1.3 + a \times DBH^b \quad (1)$$

where 1.3 is a measuring height of DBH from ground floor, and a and b are model parameters. The values of a and b were 7.29 and 0.3, respectively. Model r, R^2 , and RMSE were 0.6, 0.37, and 3.22 m, respectively (Figure A1).

The one-variable volume equation derived from DBH was used to derive the V of individual trees for the UTHF. The V equation (Equation (2)) was used for conifer species in UTHF [44]. V tariffs for broadleaf species are based on Equations (3) and (4), used for *Fraxinus* spp. with $DBH < 80$ cm and $DBH \geq 80$ cm, respectively. Similarly, Equations (5) and (6) were used for OBL species with $DBH < 80$ cm and $DBH \geq 80$ cm, respectively [45]. CST was estimated using the allometric equation (Equation (7)) [46]:

$$\text{Log } V = -3.7789 + 2.4437 \log d \quad (2)$$

$$\text{Log } V = -3.7400 + 2.4572 \log d \quad (3)$$

$$V = -12.56 + 2.265 d \quad (4)$$

$$\text{Log } V = -3.7844 + 2.4189 \log d \quad (5)$$

$$V = -8.62 + 0.190 d \quad (6)$$

$$CST = \sum_j \{ [V_j \times D_j \times BEF_j] \times (1 + R_j) \times CF \} \quad (7)$$

where d—DBH; V—stem volume for a species ($\text{m}^3 \text{ tree}^{-1}$); CST—carbon stock for a species (MgC tree^{-1}); D—wood density (t-d.m. m^{-3}); CF—dry-matter carbon fraction (MgC t-d.m.^{-1}); BEF—biomass expansion factor; R—root-to-shoot ratio; and j—tree species [46]. Table 1 shows the field data results.

Table 1. Mean value of the individual tree parameters.

Parameter	Unit	Conifer	Oak	OBL
H	m	28.05 ± 2.20 (22.57–32.87)	27.74 ± 1.74 (23.71–31.70)	25.12 ± 2.39 (19.82–30.66)
DBH	cm	52.60 ± 11.03 (29.70–84.90)	69.20 ± 13.82 (41.40–104.20)	51.32 ± 15.92 (23.20–93.80)
BA	m ² tree ^{−1}	0.23 ± 0.10 (0.07–0.57)	0.39 ± 0.16 (0.13–0.85)	0.23 ± 0.15 (0.04–0.69)
V	m ³ tree ^{−1}	1.53 ± 0.34 (0.84–2.55)	2.92 ± 2.70 (1.14–11.18)	1.44 ± 0.46 (0.62–2.68)
CST	MgC tree ^{−1}	0.47 ± 0.13 (0.23–0.84)	1.39 ± 1.28 (0.54–5.32)	0.47 ± 0.18 (0.21–1.02)

Mean value is given with ± standard deviation (minimum–maximum). H—tree height; DBH—diameter at breast height; V—stem volume; BA—basal area; CST—carbon stock; OBL—other broadleaf species.

2.3. Collection of UAV Imagery

Table 2 provides detailed information on flight parameters, UAV platforms, and sensor specifications for RGB and MS imagery collection. A DJI Matrice 300 RTK was flown to capture RGB imagery during leaf-on (October) and leaf-fall (November) seasons in 2022. In 2023, a DJI Mavic 3 Multispectral (3M) with RTK was used to capture both RGB and MS imagery during leaf-on season. Imagery collection in October for both years ensured consistency in seasonal timing. A square parallel flight plan was predesigned (Figure A2). The UAV RGB imagery collected on 8 November 2023, during the leaf fall season, was solely used for visually identifying tree species and not for metric extractions. All data collection was performed on sunny days with clear atmospheric conditions [38].

Table 2. Flight parameters and specifications for RGB and MS imagery collections using DJI Matrice 300 RTK and DJI Mavic 3M RTK.

UAV Platform *	DJI Matrice 300 RTK	DJI Mavic 3 Multispectral (3M) RTK	
Imagery	RGB imagery	RGB imagery	MS imagery
Season	Leaf-on	Leaf-on	Leaf-on
UAV battery	TB60, 6.3 kg	Li-ion battery, 651 g	Li-ion battery, 651 g
Sensor type	DJI Zenmuse P1	4/3 CMOS	1/2.8-inch CMOS
Sensor focal length	35 mm	12.29 mm	4.34 mm
Sensor pixel	45 megapixels	20 megapixels	5 megapixels
Date of collection	7 October 2022	27 October 2023	27 October 2023
Flight height	80 m	80 m	80 m
Flight speed	8–8.5 m/s	5 m/s	5 m/s
Front overlap	90%	90%	90%
Side overlap	85%	86%	86%
Image resolution	8192 × 5490 pixels	5280 × 3956 pixels	2592 × 1944 pixels
Ground resolution	0.8 cm/pixel	1.61 cm/pixel	2.8 cm/pixel

* Source: UTHF.

In mixed forests, spectral variations and shadows within heterogeneous tree crowns can result in segmentation errors, where a single tree crown may be erroneously divided into multiple crowns [4,42]. To mitigate this, the Mavic 3M drone simultaneously collected RGB and MS imagery in a single flight, ensuring consistency and eliminating shadow and illumination differences. The MS imagery captured spectral bands, including red (R), green (G), red edge (RE), and near-infrared (NIR). A total of 2798 images were collected for Mavic RGB imagery, and 3138 images were collected for Matrice RGB imagery. For MS imagery, 11,192 images were collected. Unclear and blurred images were removed for the image processing. The ground resolutions for RGB and MS imagery were 1.61 cm/pixel and

2.8 cm/pixel, respectively, with reprojection errors of 1.81 pixels for RGB and 0.60 pixels for MS imagery. Geolocation errors were 2.91 cm for RGB and 1.68 cm for MS imagery. Direct georeferencing of UAV imagery was performed without ground control points due to the dual-frequency RTK GNSS capability of UAV. This system provides highly accurate real-time location data by using satellite signals and correction data from a base station. The dual-frequency feature further improved precision by correcting for atmospheric interference, achieving centimeter-level accuracy, consistent with the findings of Htun et al. [38].

2.4. Data Analysis

2.4.1. Processing UAV Images

Figure 2 outlines the study workflow. UAV imagery was processed by the staff of UTHF using Agisoft Metashape version 1.8.4 (Agisoft LLC, St. Petersburg, Russia) and Pix4Dmapper version 4.8.0 (Lausanne, Switzerland). Sensor correction, camera calibration, and reflectance panel calibration were conducted using the respective software. Pixel values of orthomosaic images were used for analysis. Original resolutions of 0.08 m/pixel for the DJI Terra RGB orthomosaic and 0.02 m/pixel for both the DJI Mavic RGB and MS orthomosaics were resampled to 0.5 m/pixel. This resampling was performed to reduce computational load and ensure resolution consistency when combining the imagery with the CHM and Digital Terrain Model (DTM) for individual tree parameter estimation. The accuracy of the UAV-derived DTM was constrained by canopy obstruction. Therefore, a high-precision DTM was utilized, derived from an Optech ALTM Orion M300 LiDAR sensor (Teledyne Technologies, Thousand Oaks, CA, USA) attached to a helicopter in 2018, and this approach is consistent with previous studies [4,28]. This provided more accurate information on the vertical forest structure [29]. The CHM for the DJI Terra RGB flight was generated by deducting the LiDAR-derived DTM from the UAV-derived Digital Surface Model (DSM). The LiDAR DTM provided by UTHF was instrumental in this procedure [28,29]. The terrain of the forest floor remains relatively consistent over time; therefore, we used the LiDAR DTM obtained in 2018. However, since tree growth has increased over time, we used the UAV DSM to estimate the CHM in the absence of a recent LiDAR DTM for this study area. The RMSE and standard deviation of the LiDAR DTM were both 0.061 m. This indicates that both the UAV data and LiDAR DTM had low reprojection and geolocation errors, ensuring spatial consistency between them. In addition, we used spatial resolutions of 0.5 m/pixel for LiDAR DTM and UAV DSM for spatial consistency.

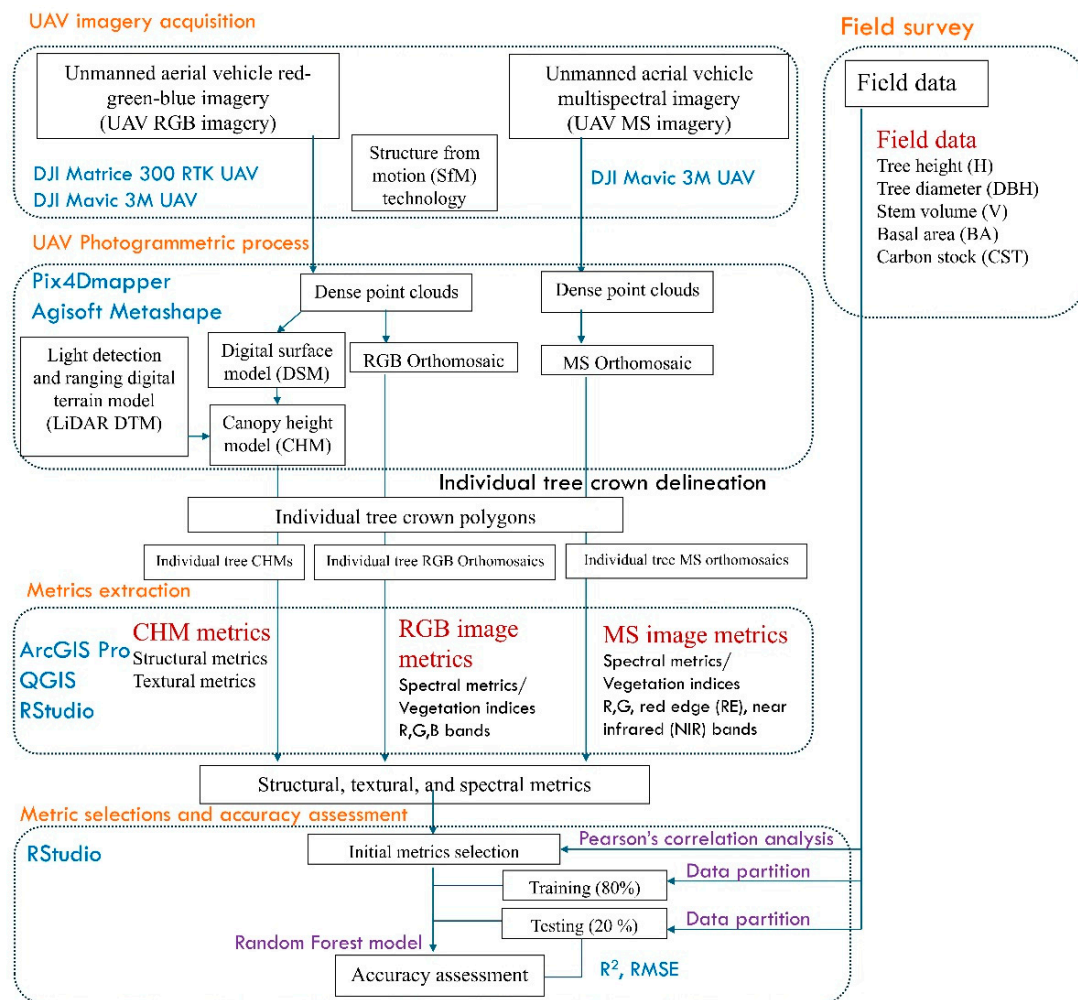


Figure 2. The study workflow included field data enumeration, UAV photogrammetry, CHM generation, and feature extraction from CHM and orthomosaic metrics. UAV—unmanned aerial vehicle; RGB—Red–Green–Blue; MS—multispectral; DSM—Digital Surface Model; SfM—Structure-from-Motion technology; RE—red edge; NIR—near-infrared.

2.4.2. Tree Crown Delineation

The spatial locations of field-measured trees, combined with visual observation of tree crowns in the UAV orthomosaic, enabled manual delineation of individual tree crowns. A high-resolution (0.8 cm/pixel) UAV RGB orthomosaic was used for clear identification where tree crown edges were more visible. Delineation was conducted using DJI Matrice RGB imagery (2022) and DJI Mavic RGB imagery (2023). Visual comparison of the tree polygons from both years showed consistent results. A paired t-test ($p < 0.05$) confirmed no significant difference in crown area (CA) between the two datasets. Therefore, tree polygons derived from the DJI Matrice RGB orthomosaic were used for metric extraction, as they were closer to the field data collection period. Tree crown delineation was straightforward for single-stem conifers but more challenging for clustered or multi-crown trees, particularly oak and other broadleaf species. Orthomosaic imagery collected during the leaf-fall season improved identification by revealing branches and upper stems, aiding in delineation in clustered canopy areas (Figure A3). Manual delineation took approximately 86 min for conifers ($n = 115$), 52 min for oak ($n = 67$), and 54 min for OBL ($n = 73$), with an average time of 46–80 s per tree crown. This included simultaneous observation of the CHM. Identifying individual tree crowns in MS orthomosaic was more challenging due to the visibility limitations of the green and red bands (Figure A4).

2.4.3. Extraction of Metrics from CHM and Orthomosaics

Table 3 summarizes the UAV-derived structural, textural, and spectral metrics. Manually delineated tree crown polygons were used to assess individual tree parameters due to the presence of multiple highly overlapping tree crowns. These polygons served as the reference for feature extraction. Structural and textural metrics were extracted from CHM (7 October 2022), while spectral metrics were derived from RGB and MS orthomosaics (27 October 2023). Spectral metrics are the vegetation indices measured by the light reflectance across wavelengths [47]. These are crucial tools in RS, providing insights into the health, structure, and productivity of vegetation across landscapes [48,49]. In forest management and inventory, spectral metrics help quantify forest attributes [49]. RGB spectral metrics are derived from R, G, and B bands, while MS spectral metrics are derived from R, G, RE, and NIR bands. The normalized difference vegetation index (NDVI) measures the reaction to chlorophyll content that resamples the vegetation growth and nutrients. Green NDVI (GNDVI) indicates the amount of water or nutrients that indicates the biomass. Leaf chlorophyll content (LCI) is related to vegetation growth and yield, disease, growth, aging, and physiological disorders. The normalized difference red edge index (NDRE) indicates the variation of chlorophyll and sugar content [34]. Textural metrics were calculated using the gray-level co-occurrence matrix (GLCM), which evaluates pixels' brightness variations in the CHM [35] to detect differences in gray levels [50,51] (Figure A5). Structural metrics such as mean, standard deviation (std), and maximum of CHM and CA values were calculated using ArcGIS Pro statistics. Textural metrics were derived with the r.texture algorithm in QGIS version 3.28 using a 3 m × 3 m window size for individual tree parameter estimation.

Table 3. The metrics derived from CHMs and RGB orthomosaics.

Sources (UAV Imagery)	Derived Metrics	Description	References
CHM structural metrics (RGB October 2022)	CA	Crown area of individual tree	[42,52]
	CHM mean	Average value of a crown pixel	[27]
	CHM max	Maximum value of a crown pixel	[53]
	CHM std	Standard deviation of the pixel per crown	
CHM textural metrics (RGB October 2022)	Angular second moment (ASM)	Homogeneity measurement of a crown	[51]
	Contrast (Cont)	Contrast of a crown image	
	Entropy (Entr), sum of entropy (SE), and difference entropy (DE)	Randomness of a crown pixels	
	Variance (Var), sum of variance (SV), and difference variance (DV)	Gray tone variance of a crown	
	Correlation (Corr)	Linear dependency of a crown pixels	
	Sum of average (SA)	Distribution of sum values of a crown pixels	
	Information measures of correlation (MOC1 or MOC2)	A measure to evaluate the complexity, MOC1 differs from MOC2 based on different normalization or weighting	
MS spectral metrics (MS October 2023)	Inverse Difference Moment (IDM)	Local homogeneity of a crown image	[34]
	Normalized difference vegetation index (NDVI)	$(NIR - R)/(NIR + R)$	
	Normalized difference red edge (NDRE)	$(NIR - RE)/(NIR + RE)$	
	Leaf Chlorophyll Index (LCI)	$NIR/(Green - 1)$	
	Green NDVI (GNDVI)	$(NIR - Green)/(NIR + Green)$	

Table 3. Cont.

Sources (UAV Imagery)	Derived Metrics	Description	References
RGB spectral metrics (RGB October 2023)	Red, Green, Blue	R, G, B	[54]
	Brightness (Bright)	$((R^2 + G^2 + B^2)/3)^2$	[55]
	Mean brightness (m_Bright)	$(R + G + B)/3$	[54]
	Green-to-Red Ratio (G_R)	G/R	[54]
	Blue-to-Red Ratio (R_B)	B/R	[56]
	Blue-to-Green Ratio (B_G)	B/G	[57]
	Normalized Green (nG)	$G/(R + G + B)$	[54]
	Normalized Red (nR)	$R/(R + G + B)$	[58]
	Normalized Blue (nB)	$B/(R + G + B)$	[58]
	Normalized G-B-VI (nGBVI)	$(G - B)/(G + B)$	[59]
	Normalized G-R-VI (nGRVI)	$(G - R)/(G + R)$	[54]
	Normalized R-B-VI (nRBVI)	$(R - B)/(R + B)$	[60]
	Modified G-B VI (MGBI)	$(GG - RR)/(GG + RR)$	[61]
	Visible-band Difference VI (VDVI)	$(2G - R - B)/(2G + R + B)$	[62]
	Excess Green Index (EGI)	$2G - R - B$	[63]
	Visible Atmospherically Resistant Index (VARI)	$(G - R)/(G + R - B)$	[64]

RGB—Red, Green, and Blue; MS—multispectral; max—maximum; std—standard deviation; n—normalized.

2.4.4. Random Forest Estimation and Accuracy Assessment

Individual tree parameters measured in the field were compared with structural, textural, and spectral metrics, as well as their combination, using the RF regression model. The RF algorithm is widely employed in RS due to its robustness and capacity to handle randomness [65]. The RF model was applied using the “randomForest” package (version 4.7–1.1) in RStudio version 4.22. Key parameters such as mtry and ntree were optimized within the model [28,53] to achieve the high R^2 and low RMSE. Metrics were ranked by their importance using the percent increase in mean squared error (%IncMSE) and in node purity (IncNodePurity). %IncMSE was prioritized for metric selection. The error tends to increase when random variables are substituted.

Despite the usage of a large number of variables, identifying the most important structural, textural, and spectral metrics is crucial. Dimensionality reduction is essential for selecting relevant RS metrics and avoiding multicollinearity. To address the multicollinearity and identify the most relevant RS metrics, a two-step approach was applied: Firstly, we performed the Pearson’s correlation test using the “metan” package. Metrics negatively correlated (p at 0.05) with field-measured individual tree parameters were removed [28]. Secondly, category-specific RF analysis was performed. Structural, textural, and spectral metrics were analyzed in the RF model to eliminate the least important metrics. The most important metrics from each category were combined, and the top ten metrics were selected through further RF analysis. The RF model also inherently performs dimensionality reduction through out-of-bag (OOB) validation, ranking variable importance [66]. The dataset was split into training (80%) and testing (20%). The model was fine-tuned by iteratively removing the least important metrics to achieve the best accuracy, and the final set of metrics was chosen for estimating individual tree parameters. RMSE and R^2 were used together for prediction accuracy [67].

3. Results

3.1. The Tree Crown Delineation and CHM Extraction

Figure 3 illustrates the results of individual tree crown delineation and CHM extraction for conifer, oak, and OBL species. The mean CA for conifer, oak, and OBL was $37.11 \pm 16.12 \text{ m}^2$ ($n = 115$), $121.78 \pm 49.88 \text{ m}^2$ ($n = 67$), and $66.96 \pm 46.08 \text{ m}^2$ ($n = 73$), respectively. The CHM accuracy was evaluated by comparing CHM maximum with field-

measured H of conifer trees. The comparison showed high accuracy ($R^2 = 0.86$, $r = 0.93$, $RMSE = 2.15$ m, $\%RMSE = 7.68$, $n = 52$; Figure 3c).

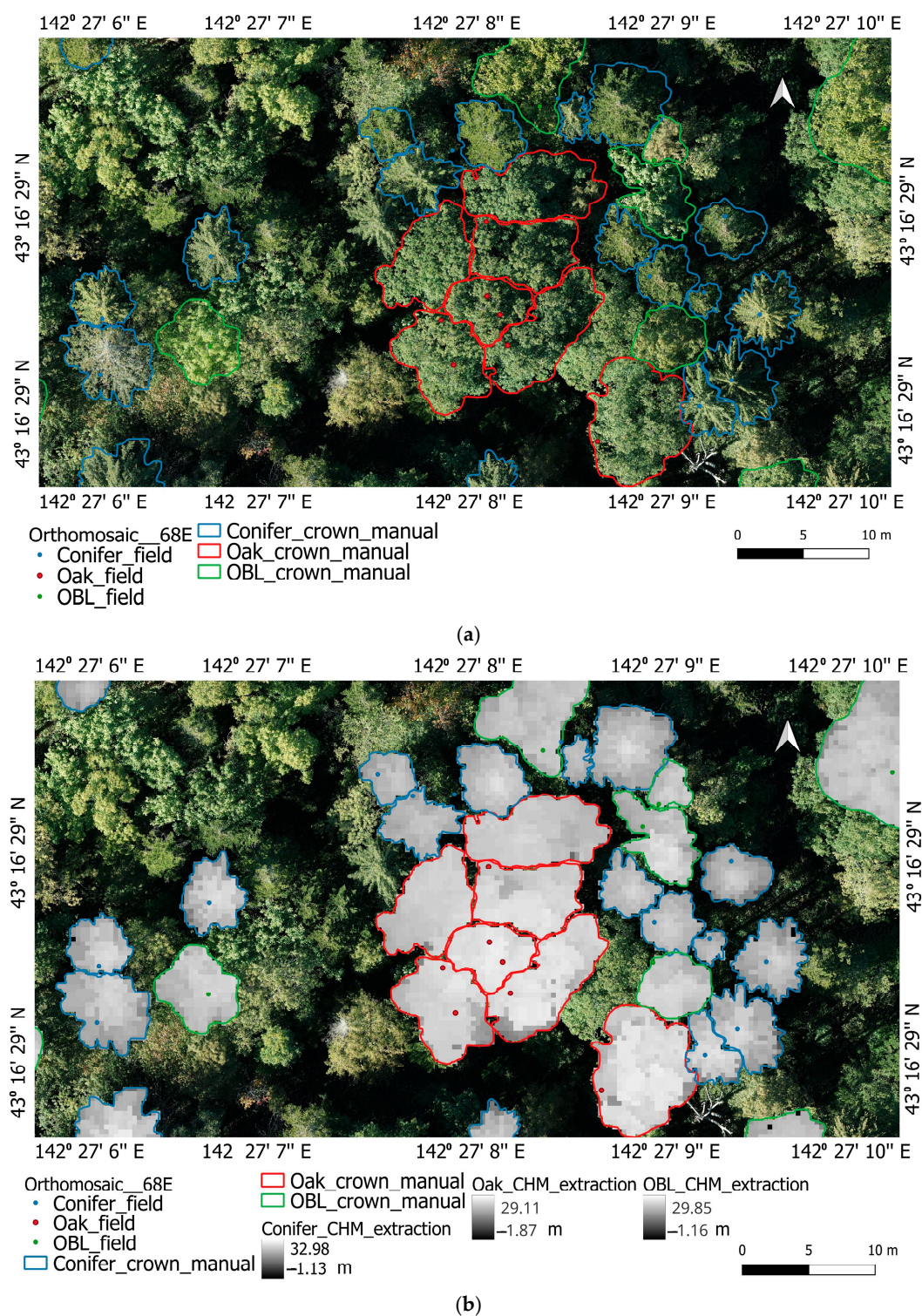


Figure 3. Cont.

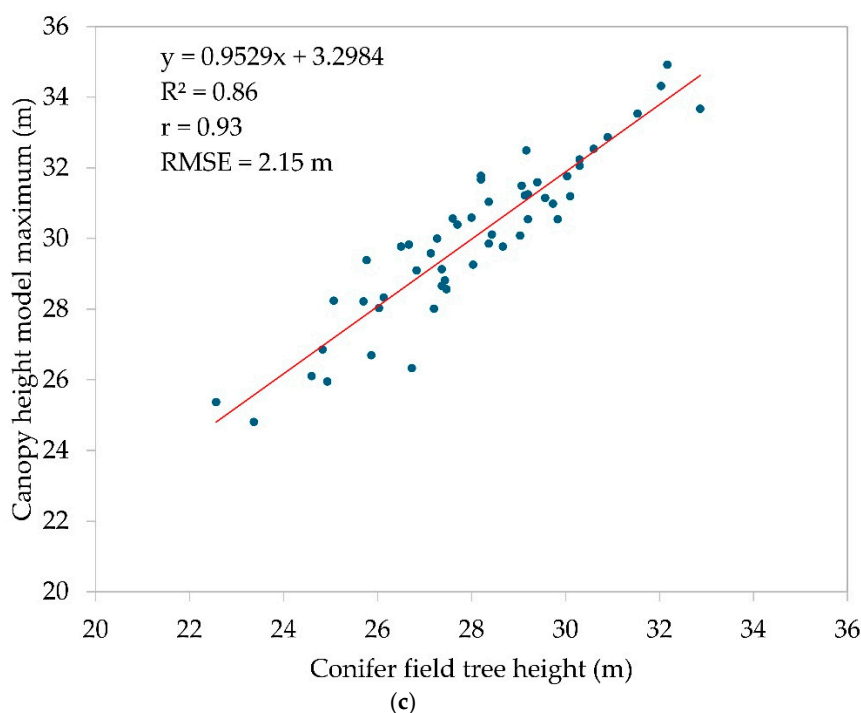


Figure 3. The individual tree crown delineation and CHM extraction of conifer, oak, and OBL with the field tree geospatial location: (a) manual crown delineation of conifer, oak, and OBL; (b) individual CHM extraction of conifer, oak, and OBL with the field tree geospatial location. (c) A linear relationship between conifer field tree height (H) and canopy height maximum (CHM max).

3.2. Variable Selection for Individual Tree Parameters

Figure 4 displays the top ten metrics, along with the final selected metrics by the RF model, using a combination of structural, textural, and spectral metrics. CA was the most significant metric for predicting individual parameters (H, DBH, BA, V, and CST). For conifer H prediction, structural (CHM max and CHM mean), textural (SA, ASM, and SV), and spectral metrics (NDVI, GNDVI, and G_R) were selected. Structural metrics such as CHM max, CHM mean, and CA had the greatest contribution to estimating individual tree parameters, followed by textural and spectral metrics (Figure 4, first row). For oak and OBL H prediction, CA and CHM std were important structural metrics, with additional contribution from textural and spectral metrics. For oak, CA contributed to estimating DBH and BA, while CA and CHM_std were important for V and CST. For OBL, CA and textural metrics contributed to estimating DBH, BA, V, and CST, with spectral metrics excluded in some cases.

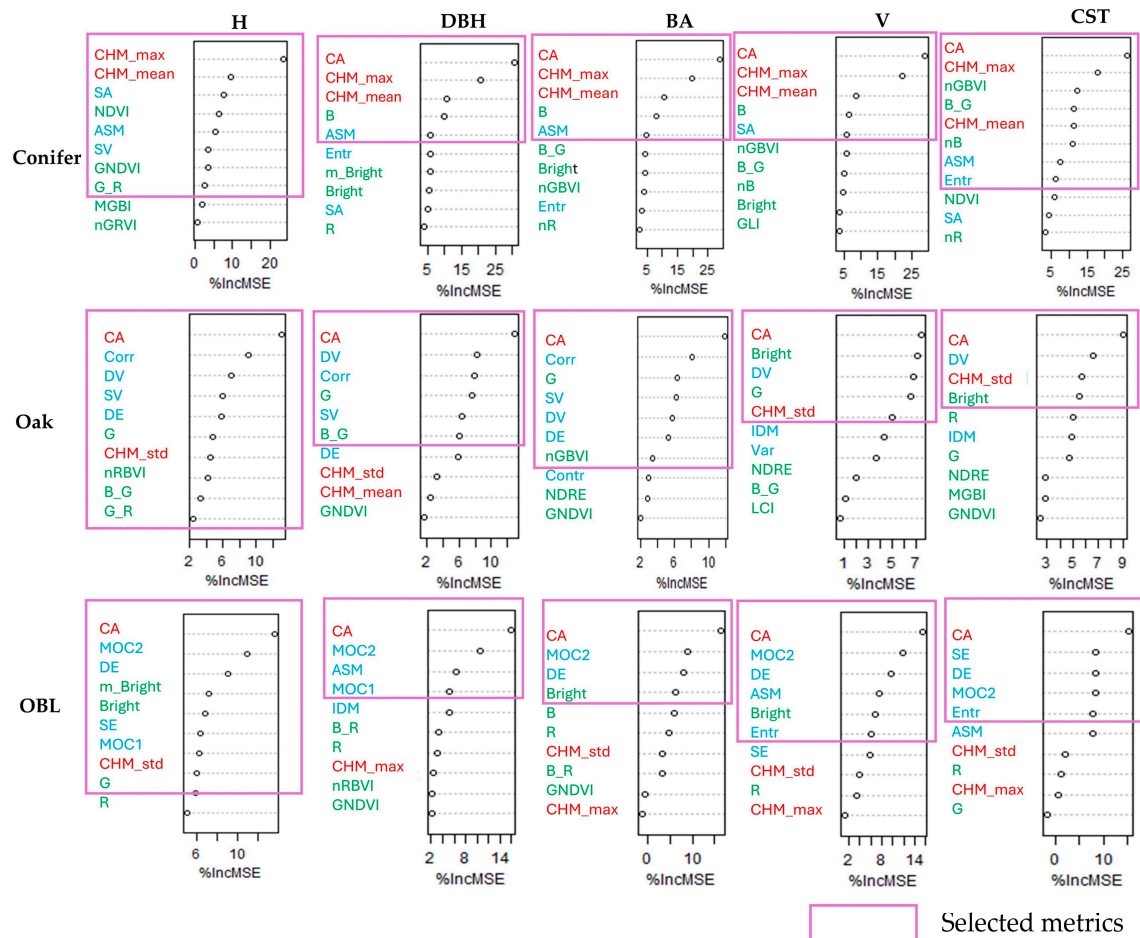


Figure 4. The top ten UAV metrics with finally selected metrics (purple box) by RF model in combined metrics from structural (red-color font), textural (blue-color font), and spectral metrics (green-color font): left to right, RF model column shows variable importance selection for H, DBH, BA, V, and CST. From top to bottom, rows show the results of variable-importance selection for conifer, oak, and OBL.

3.3. Accuracy of Individual Tree Parameters

Table 4 presents the accuracy of individual tree parameters—H, DBH, BA, V, and CST—for conifer, oak, and OBL species using structural, textural, spectral, and combined metrics. Figure 5 compares field-measured individual tree parameters with those predicted by UAV metrics. Overall, combined metrics provided the highest accuracy for all parameters, outperforming individual metric categories. Conifer species showed higher accuracy than oak and OBL species.

For H, combined metrics showed higher accuracy for conifer ($R^2 = 0.89$, RMSE = 0.85 m), followed by oak ($R^2 = 0.47$, RMSE = 1.54 m) and OBL ($R^2 = 0.46$, RMSE = 1.71 m). Similarly, DBH accuracy was highest for conifer ($R^2 = 0.70$, RMSE = 6.05 cm), followed by oak ($R^2 = 0.49$, RMSE = 11.12 cm) and OBL ($R^2 = 0.38$, RMSE = 12.48 cm). Conifer had the highest accuracy for BA ($R^2 = 0.70$, RMSE = 0.05 m² tree⁻¹), followed by OBL ($R^2 = 0.57$, RMSE = 0.08 m² tree⁻¹) and oak ($R^2 = 0.44$, RMSE = 0.14 m² tree⁻¹). For V, conifer showed the highest accuracy ($R^2 = 0.72$, RMSE = 0.07 m³ tree⁻¹), followed by OBL ($R^2 = 0.51$, RMSE = 0.27 m³ tree⁻¹) and oak ($R^2 = 0.11$, RMSE = 2.56 m³ tree⁻¹). For CST, conifer had the highest accuracy ($R^2 = 0.79$, RMSE = 0.06 MgC tree⁻¹), followed by OBL ($R^2 = 0.38$, RMSE = 0.14 MgC tree⁻¹) and oak ($R^2 = 0.37$, RMSE = 1.00 MgC tree⁻¹).

Table 4. The accuracy of individual tree parameter estimation of H, DBH, BA, V, and CST for conifer, oak, and OBL at structural, textural, spectral, and combined metrics, using RF regression model.

Individual Tree Parameters (Unit)	Species	Structural		Textural		Spectral		Combined	
		R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE
H (m)	Conifer	0.87	0.86	0.63	1.42	0.38	1.84	0.89	0.85
	Oak	0.43	1.90	0.33	2.01	0.06	2.23	0.47	1.54
	OBL	0.38	1.89	0.32	1.96	0.18	2.26	0.46	1.71
DBH (cm)	Conifer	0.66	6.58	0.26	9.46	0.11	10.53	0.70	6.05
	Oak	0.29	12.91	0.29	12.95	0.04	13.99	0.49	11.12
	OBL	0.36	12.25	0.21	13.63	0.22	13.57	0.38	12.48
BA (m ² tree ^{−1})	Conifer	0.67	0.06	0.19	0.09	0.07	0.10	0.70	0.05
	Oak	0.39	0.15	0.31	0.16	0.04	0.16	0.44	0.14
	OBL	0.41	0.09	0.18	0.11	0.14	0.12	0.57	0.08
V (m ³ tree ^{−1})	Conifer	0.66	0.21	0.25	0.30	0.09	0.33	0.72	0.07
	Oak	0.02	3.36	0.07	3.27	0.07	2.89	0.11	2.56
	OBL	0.22	0.41	0.36	0.31	0.30	0.33	0.51	0.27
CST (MgC tree ^{−1})	Conifer	0.53	0.09	0.38	0.10	0.23	0.11	0.79	0.06
	Oak	0.05	1.33	0.11	1.53	0.01	1.41	0.37	1.00
	OBL	0.29	0.16	0.25	0.16	0.05	0.21	0.38	0.14

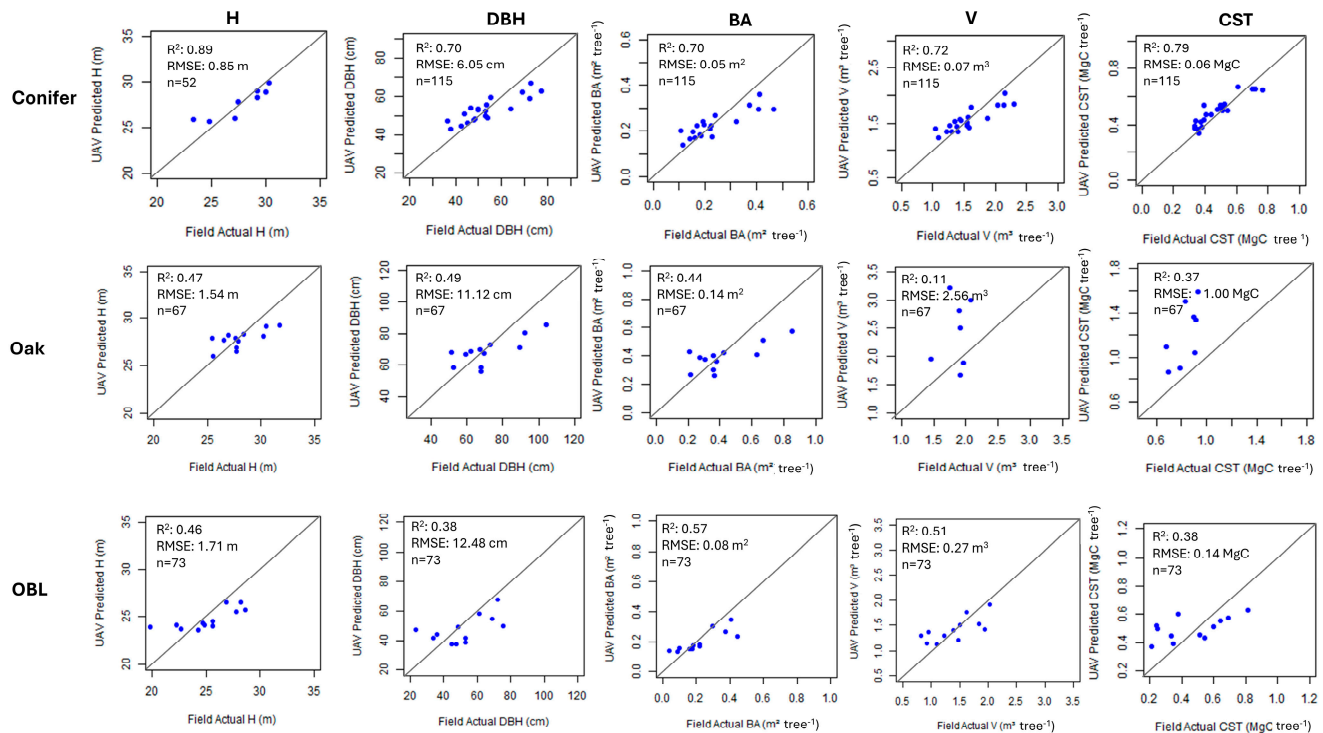


Figure 5. The results of the field-measured individual tree parameters versus UAV-predicted individual tree parameters: From left to right, figure illustrates the individuals tree parameters of H, DBH, BA, V, and CST. From top to bottom, figure illustrates the results of individual tree parameters for conifer, oak, and OBL.

4. Discussion

4.1. Tree Crown Delineation and CHM Extraction

Tree crown delineation and CHM extraction are more challenging in complex, dense, and mixed forests compared to simpler, even-aged forests or monoculture plantations [4,37,38,52]. High-resolution orthomosaic, combined with leaf-fall-season imagery enabled accurate manual delineation of tree crowns in this study's complex forest. Manual delineation is effective for estimating individual tree parameters in smaller-to-medium-

sized forests but remains challenging for large-scale applications. It is, however, crucial for validating automated tree crown segmentation in larger areas. This study aimed to assess whether combined UAV-derived metrics could accurately estimate individual tree parameters, justifying manual delineation. Previous research found automated segmentation methods, such as watershed and multiresolution segmentation, less accurate in complex forests [37,42]. Moving forward, we will explore robust segmentation methods for complex forests and improve automated approaches for larger areas. With improved segmentation accuracy, manually delineated tree crowns can be scaled up for individual tree parameter estimation in larger areas.

4.2. Variable Selection for Estimating Individual Tree Parameters

The structural metric CA contributed to estimating all individual parameters except for conifer H. CA reflects the distribution of individual canopies, with all other metrics derived from it [42,52]. For conifer, CHM maximum and mean also played a key role in estimating individual tree parameters. Structural metrics, especially those related to height, were more influential in estimating H and DBH than spectral metrics [4,68]. Previous studies have highlighted the LiDAR-based height and crown metrics for estimating BA and V [12,69].

Textural metrics varied by species. High value of entropy (Entr), information measures of correlation (MOC), variance (Var), difference entropy (DE), and difference variance (DV) indicated greater canopy variation, while high angular second moment (ASM) suggested a more uniform canopy structure [35,70]. For conifer species, sum of average (SA) and ASM were textural metrics [35], reflecting homogeneity of conifer crowns. For oak species, textural metrics like correlation (Corr), sum of variance (SV), and DV indicated a greater complexity [35,70], reflecting more variation in oak crowns. For OBL, MOC and Entr were key textural metrics, suggesting complex canopy structure [70]. Karthigesu et al. [28] found that broadleaf-dominated forests showed greater complexity than conifer-dominated ones, with textural metrics such as DV, Entr, DE, and Var contributing the most. Incorporating textural metrics alongside structural ones improved parameter estimation accuracy [49]. In this study, we selected contrast (Cont) and angular second moment (ASM) instead of dissimilarity to avoid redundancy in metrics with similar characteristics.

Spectral metrics extracted from UAV RGB and MS imagery were also crucial for estimating individual tree parameters. The selected spectral metrics—G, B, B_G, G_R, nR, nGBVI, NDVI, and GNDVI—were derived from R, G, B, and NIR, which significantly influenced tree parameter predictions. NDVI, for example, characterizes canopy vigor [71,72], while the R and B wavelengths are important for tree growth [73]. Multispectral indices using NIR and RE wavelengths have strong relationships with tree biomass, which correlates with tree growth and biomass increment [74,75]. These bands also affect tree vigor parameters [34].

4.3. Accuracy of Individual Tree Parameter Estimations

Zhou and Zhang [1] reported the R^2 range of 0.74–0.89 for conifer species using UAV RGB oblique imagery, consistent with our findings for conifers. Moe et al. [4] obtained lower accuracy for oak ($R^2 = 0.10$, RMSE = 1.96 m) and monarch birch ($R^2 = 0.27$, RMSE = 1.77 m), along with lower accuracy for broadleaved trees in mixed conifer–broadleaf forests, due to crown overlap and complexity. Conifer crowns, with their conical shape, are easier to identify in the field, whereas a spherical shape with multiple treetops of broadleaf crowns complicates treetop identification, leading to lower accuracy of H in broadleaf species [4,11,69,76–78].

We applied a nonlinear model for H and DBH using data ($n = 216$) from similar forest compartments, which reduced uncertainty. However, increasing sample sizes for each broadleaf species would improve the species-specific model accuracy. Despite overall accuracy, H for conifer, oak, and OBL was underestimated, likely due to the mixed conifer–broadleaf forest structure [79], limited samples size, and measurement error [67]. Underestimation may also occur when the CHM is lower than the field H due to the SfM's inability to detect precise treetops [52,67].

DBH accuracy in this study was similar to that of Moe et al. [4] for oak ($R^2 = 0.40$, RMSE = 13.29) and OBL ($R^2 = 0.56$ – 0.60 , RMSE = 7.30–8.51); and it was comparable to that of Shrestha and Wynne [80] for conifers ($R^2 = 0.74$, RMSE = 6.60). However, DBH for oak and OBL was underestimated, likely due to the clustering of trees in the study area, which resulted in smaller delineated crowns. As BA is derived from DBH, it followed a similar trend.

Conifer CST accuracy was comparable to biomass accuracy ($CST = biomass \times 0.51$) [46] reported by Zhou and Zhang [1] ($R^2 = 0.81$ – 0.87). A wide range of accuracy values has been reported for data fusion approaches using LiDAR and optical sensors for biomass ($R^2 = 0.33$ – 0.82) and volume ($R^2 = 0.39$ – 0.87) estimation [25]. The horizontal and vertical distribution of tree crowns in broadleaf species leads to higher variation, which affects the accuracy of V and CST estimations [81,82]. The distribution of tree crowns differs between broadleaf and conifer species due to their growth patterns and species characteristics [76,83]. Broadleaf trees utilize large gaps and tend to spread their crowns both horizontally and vertically to occupy available open space as quickly as possible. Once the horizontal distribution of the tree crown reaches its maximum, growth continues more in the vertical direction. This growth pattern often results in broadleaf species having highly overlapping and multiple crowns in a mixed conifer–broadleaf forest. This could be one of the reasons for lower accuracy in estimating individual tree parameters, as there is a weaker relationship between crown area (CA) and other metrics.

In this study, oak's V and CST were overestimated compared to OBL species (Figure 5), resulting in multiple tree crowns. This increased variation (higher RMSE for V = 2.56 and CST = 1.00) compared to OBL and conifer (Table 3). The value of CA for oak is extremely high (121 m^2), followed by OBL (66 m^2) and conifer (37 m^2), indicating greater variation in oak tree crowns. For oak, textural metrics DV and CHM-std, along with CA, were key predictors for CST and V, reflecting the highest variation within the oak crown [28,49,70].

5. Conclusions

This study estimated individual tree parameters—H, DBH, BA, V, and CST—in a complex mixed conifer–broadleaf forest using a combination of structural, textural, and spectral metrics extracted from high-resolution UAV RGB and MS imagery, coupled with an RF model. The integration of RGB and MS imagery with a combination of structural, textural, and spectral metrics introduced a novel approach to estimating these parameters. High-resolution orthomosaic and CHM, combined with leaf-fall-season imagery, enabled manual delineation of individual tree crowns in complex mixed conifer–broadleaf forests characterized by multiple overlapping tree crowns. Combining these metrics significantly improved estimation accuracy, particularly for conifer species ($R^2 > 0.7$), with structural metrics being most influential, followed by textural and spectral metrics. For oak and OBL species, all three metrics contributed equally, improving accuracy ($R^2 < 0.57$) compared to previous studies.

The findings offer valuable insight for pre-selecting high-value species before field investigation using UAV photogrammetry in mixed conifer–broadleaf forests. This approach supports selective harvesting, forest inventory, carbon stock estimation, species-specific

management, silvicultural planning, and cost-effective forest monitoring. Species exhibit unique spectral, textural, and structural traits, making the integration of RGB and MS imagery particularly advantageous for species-level parameter estimation. Traditional ground surveys require significant time to estimate individual tree parameters, particularly tree height, which often requires multiple measurements for accuracy. Measuring tree height for broadleaf species is especially challenging in complex forests. However, integration of UAV-derived metrics enabled the forestry practitioners to estimate these parameters without conducting extensive field inventories. Additionally, accessing remote areas for field measurements is difficult, but UAV photogrammetry overcomes this challenge. Due to the time-consuming and labor-intensive nature of traditional surveys, they are not conducted frequently. In contrast, UAV imagery allows for more frequent data collection, facilitating regular forest inventory updates. Our integrated approach significantly contributes to forest inventory data collection, which is essential for sustainable forest management. Challenges such as canopy overlap in dense forests were addressed using high-resolution RGB imagery to improve crown delineation, and optimal flight conditions were used to minimize shadows, motion blur, and spectral inconsistencies. UAVs with RTK GNSS and gimbal-stabilized cameras, combined with overlapping flight paths (90% front and 85–86% side overlap), ensured image stability and reconstruction accuracy.

Although the estimation accuracy of individual tree parameters was improved, several limitations persist in this study. Estimation accuracy was higher for conifer species, while broadleaf species presented challenges in mixed conifer–broadleaf forest due to overlapping, clustered, and multiple tree crowns. Manual crown delineation is labor-intensive, requiring species-specific knowledge. Developing automated and more robust methods for individual tree crown delineation should be prioritized, particularly in areas where trees are dense and complex and in mixed forests with highly overlapping, clustered, and multiple tree crowns. Future research should focus on increasing sample sizes, particularly for oak and OBL species, to create a balanced dataset for training and testing, improving model generality. The integration of multisource RS technologies such as LiDAR, UAV-based multispectral and hyperspectral imagery, and deep-learning algorithms can enhance automatic tree crown delineation and rapid individual tree detection in densely clustered, highly overlapped complex forests with multiple crowns. Such advancements will address current limitations and further improve estimation accuracy for individual tree parameters.

Author Contributions: Conceptualization, methodology, data analysis, writing—original manuscript, and revisions, J.K.; supervision, resources, writing—review and editing, project administration, and funding acquisition, T.O.; writing—review and editing, S.T.; writing—review and editing, T.H. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable.

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Data Availability Statement: The field and UAV datasets from this study are not publicly available due to site sensitivity and forest management practices involved, and these datasets belong to the University of Tokyo Hokkaido Forest. However, these datasets are available upon request to the corresponding author with reasonable justification.

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

Appendix A

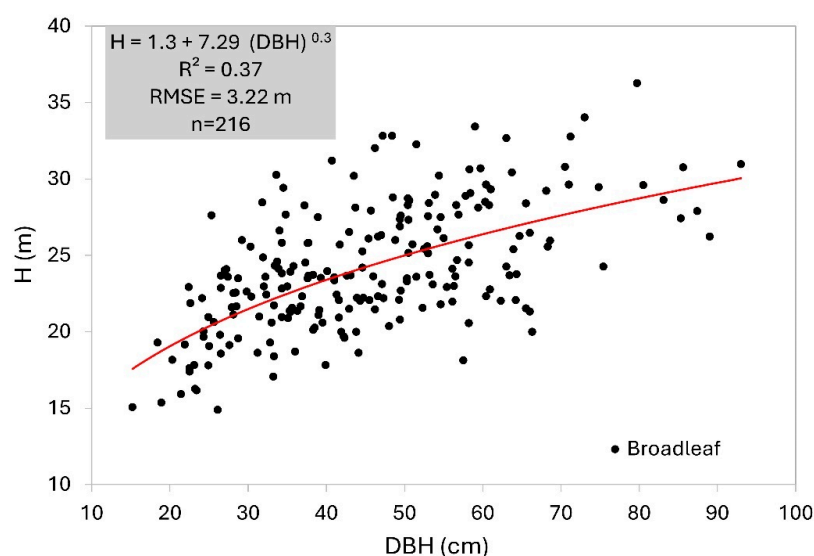


Figure A1. The H-DBH model for broadleaf species derived from 216 trees in the compartments of 16, 65–66, and 03. Model parameters a and b were 7.29 and 0.3, respectively.

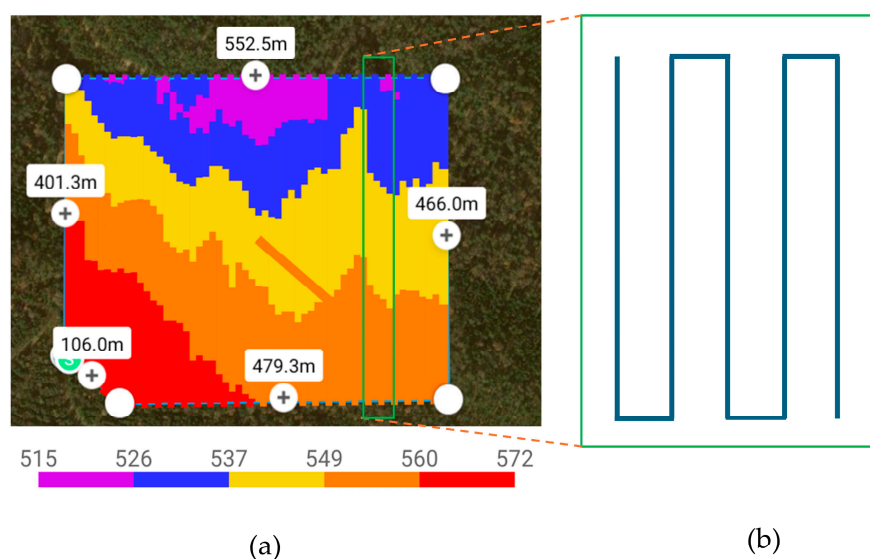


Figure A2. The flight plan of UAV: (a) flight plan map visible at the controller screen and (b) a zoomed-in portion of flight plan. Elevation of the study area indicated by the legend showing different colors; the plus (+) sign, with a value in m, represents the length of one side of the flight area.

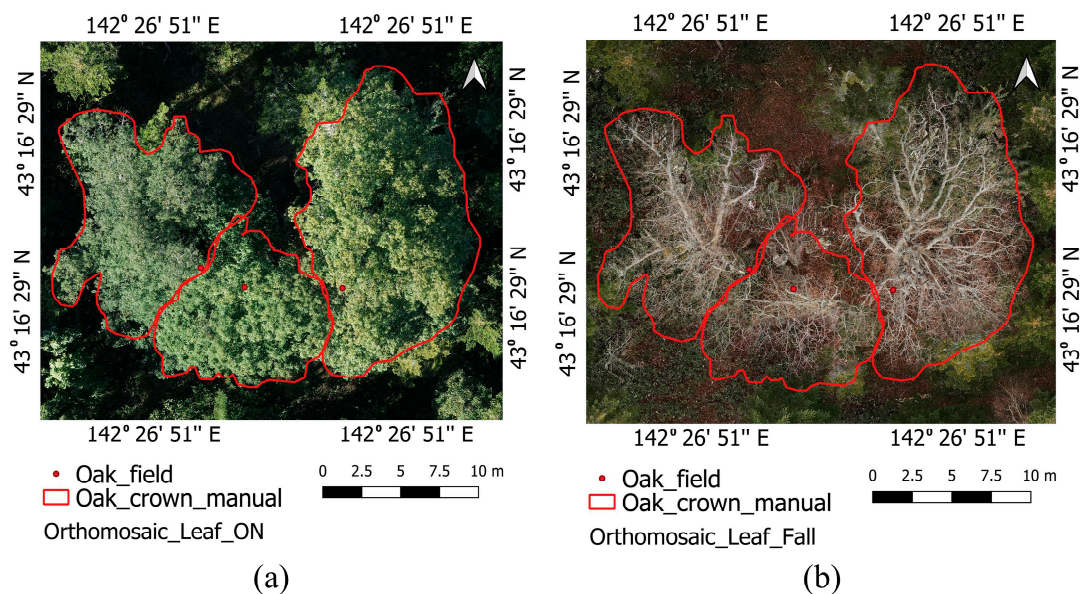


Figure A3. The manually delineated individual tree crowns (red lines), along with a spatial position of trees (red dots) in a clustered canopy area in RGB orthomosaic: (a) visibility of oak tree crowns in leaf-on seasons (7 October 2023) and (b) visibility of oak tree stem in leaf-fall seasons (8 November 2023).

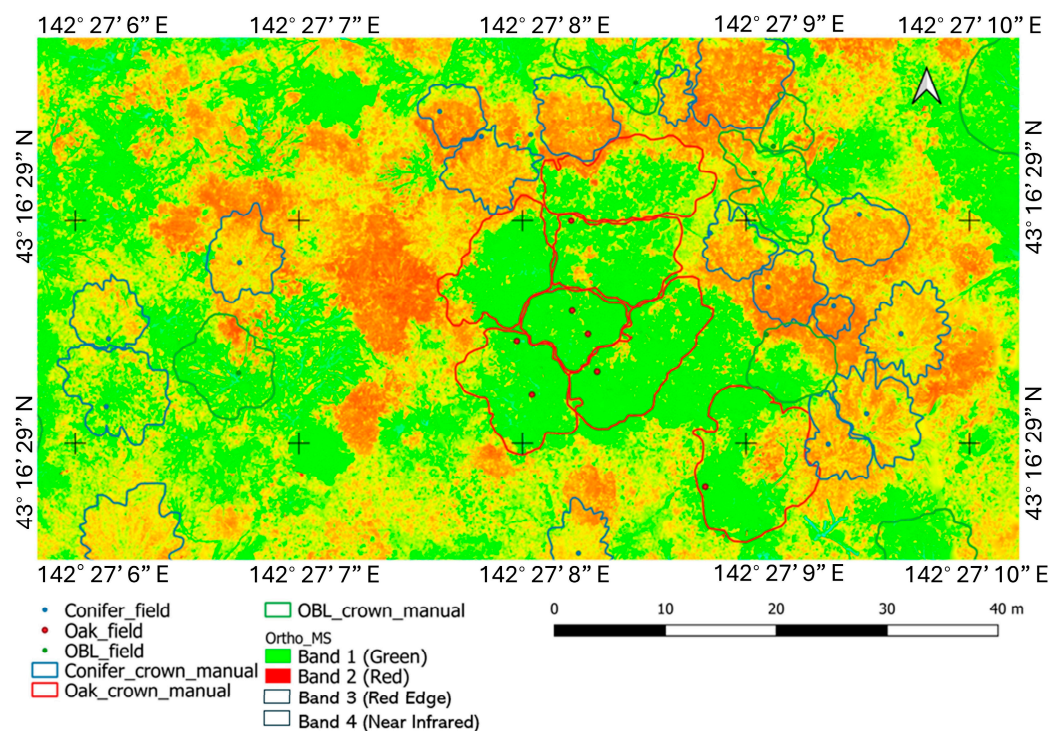


Figure A4. The individual tree crowns and their geospatial locations for conifer, oak, and OBL in MS orthomosaic. The color distributions in the figure are based on the default settings of Band 1 and Band 2 in QGIS software.

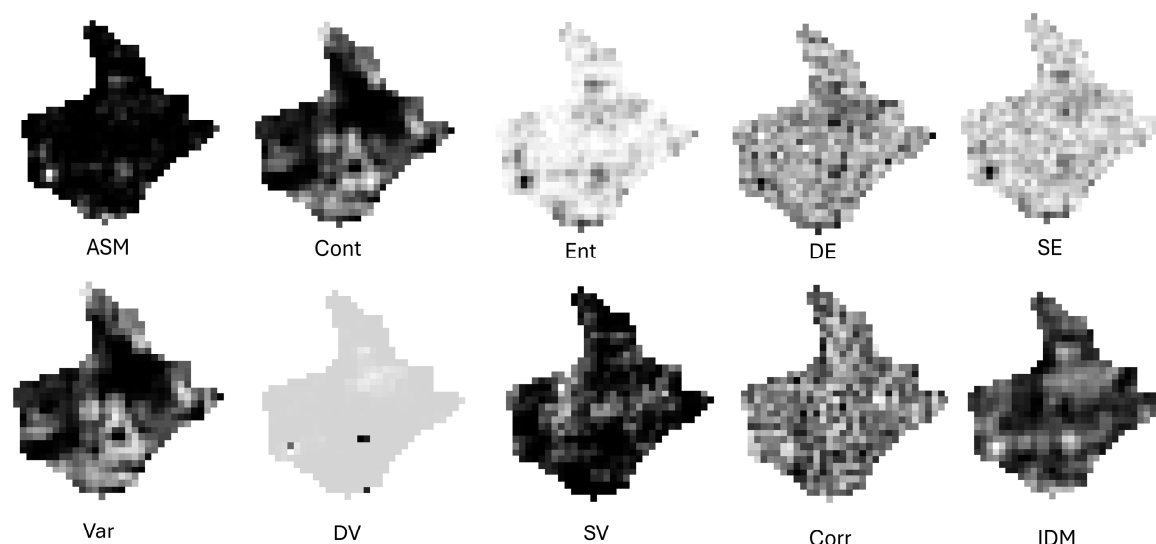


Figure A5. The visibility of textural metrics of an individual tree crown, e.g., broadleaf species.

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