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Construction of Tree-based Forest Management Digital Twin Database with Airborne Laser Surveying

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Recently, in the forestry sector, the carbon fixation capacity of forests has been highlighted for climate change response. In addition, the need for reliable forest management information is increasing for large-scale forest disaster response such as landslides and forest fires. In order to generate essential data for forest management, horizontal structure surveys, such as tree species and forest type, and vertical structure surveys, such as tree height and diameter at breast height (*DBH*), must be conducted. In this study, a comprehensive survey method using multisensor airborne LiDAR surveying was introduced for Chiaksan National Park (8.32 km^2), which is a natural forest. The forest survey method applied in this study was a two-step method that performed object-based forest type classification using high-resolution orthoimages, and then performed individual tree detection (ITD) for each forest using high-density ALS data. As a result of this study, object-based forest type classification using orthophotos showed a classification accuracy of more than 95% for both coniferous and deciduous trees. In addition, in the ITD of natural forests by forest type, the quality of conifers was good, but the ITD quality was higher than 73%. In this process, a method for generating essential data for tree-based forest management, such as tree height and *DBH*, was established. In addition, we established a process for calculating the stem volume, biomass, and carbon storage capacity of the extracted trees, and created a total of 18 forest management digital twin databases for all trees in the research area. The tree-based forest management digital twin database for national park natural forests constructed through this study was used for the 2D and 3D visualization of various forest management information as well as for the demonstration construction of a forest management digital twin pilot system. Such a tree-based forest management digital twin can quickly confirm more accurate information necessary for forest management by tree unit, so it is expected to be efficiently utilized for establishing a carbon neutrality transition strategy as well as for simulating forest disasters for the conservation management of forest resources.

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1. Introduction

Currently, climate change and global warming are causing frequent natural disasters worldwide, such as heat waves, heavy snow, extreme rain, and wildfires. To address this, the intergovernmental panel on climate change (IPCC) strongly recommends carbon neutrality.

Forest resources, as efficient carbon sinks and powerful nature-based solutions, require urgent, scientifically sound conservation and management.(1) Accurate forest resource management is essential to achieve carbon neutrality and effectively mitigate large-scale forest disasters.

Forest resource management data are classified into horizontal data, such as tree species or tree type, and vertical data, such as tree height (*H*) and diameter at breast height (*DBH*). The general method for obtaining forest management information involves conducting surveys using a 30 × 30 m^2 area-based approach (ABA).

The data obtained through ABA is used to calculate forest information for the entire area by considering tree species and multiplying by their respective areas. This area-based survey method determines the quality of data depending on the researcher's skill level, and it is a labor-intensive method that requires a lot of time and effort.(2) Moreover, there is a problem that the accuracy of H is significantly reduced compared with that of *DBH*.

Recently, ways to introduce various LiDAR technologies have been studied to mitigate the problems of ABA forest surveys. As for LiDAR technology applied to forest surveys, terrestrial laser scanning (TLS) technology was first used for forest inventory in the survey area (plot) to address the problems of field surveys focusing on manpower. Recently, it has progressed to performing individual tree detection (ITD) on the entire forest through airborne laser scanning (ALS) technology and generating forest management data using individual trees.

LiDAR technology, first introduced for forest inventory, was primarily an alternative to existing manpower-intensive surveys. The mainstay was drone laser scanning (DLS) technology with LiDAR sensors mounted on rotary-wing drones, as well as handheld and backpack-type ground LiDAR technologies. This technology helps to address the issues of existing research methods that heavily rely on manpower.(3–6)

However, while drone LiDAR and ground LiDAR technologies can precisely measure individual trees within the survey range, making them suitable alternatives to manpower-focused survey methods, they have limitations that prevent them from conducting a complete survey of large forest areas.

On the other hand, studies on the utility of ALS technology for forest inventory were conducted prior to the development of TLS. Since ALS uses aircraft, it has the advantage of quickly measuring large areas. As a result, extensive research is being conducted on ITD using ALS data.(7–9)

In addition, in the past, ALS technology had the disadvantage of low point density, making it difficult to detect, extract, or conduct detailed ITD. However, it has recently become possible to acquire high-density point cloud data (PCD) of more than 40 points per square meter, a significant improvement over the past, although still not at the level of terrestrial LiDAR. As a result, more precise forest information than before can now be obtained.

To date, research results that have provided individual tree-based forest management data for large areas of natural forests using high-density ALS data are extremely limited. Additionally, research related to building digital twins for individual tree management is still in its early stages.

Therefore, in this study, we established a method for generating individual tree-based forest management data using airborne LiDAR data to support decision-making based on scientific data in forest-related public policy processes, such as climate crisis response and various forest disasters.

This method was applied to the natural forest of Chiaksan National Park (8.32 km² in Bugok District) to build a digital twin database for individual tree-based forest management, generating 18 types of data for each tree through ITD.

In this study, as shown in Fig. 1, using an orthoimage generated by the computer vision (CV) analysis of five-way digital images from the airborne LiDAR survey results, we classified trees in the study area into coniferous and broad-leaved forests by applying object-based forest type classification. These classifications were then converted into vectors and used to analyze the horizontal structure of the forest.

In the vertical structure analysis of the forest, the optimal ITD methodology[10] for each forest type was established on the basis of ALS data with a point density of 40 or more. The quality of ITD by forest type was analyzed through recall, precision, and $F1$ score using the TLS performance of six plots.

In addition, the *DBH* was determined through a nonlinear regression equation based on the height of each tree determined during the ITD, and a process was established to calculate stem volume, biomass, and carbon storage capacity for individual trees.

In this way, the natural forest-based ITD and forest management data generation methodology established through this study was applied throughout the Chiaksan National Park Bugok District (8.32 km²) to build 18 forest management information databases for each tree.

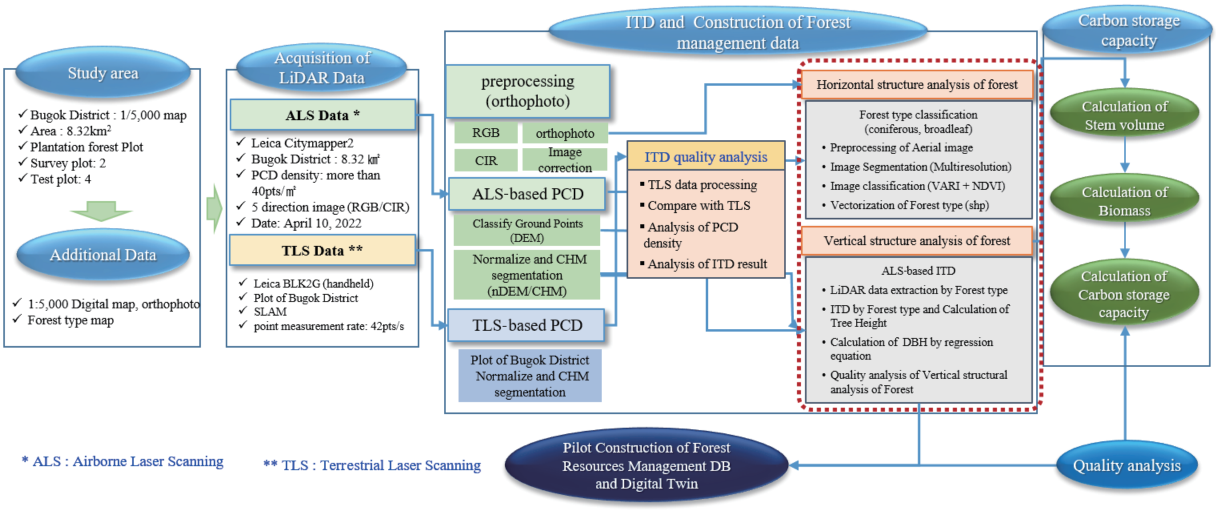


Fig. 1. (Color online) Main process of this study.

Additionally, a forest management digital twin was built on a pilot basis using a 3D tree model. Through this, the forest management digital twin database is expected to be used as basic data for forest conservation and management in the future, and to support decision-making in scientific public policy processes.

2. Materials and Methods

2.1 Description of study site

The Bugok District within Chiaksan National Park, the subject of this study, is a nationally protected area and is thoroughly managed by the Korea National Park Service. It is less exposed to external influences, such as thinning or human intervention, thus maintaining its complex natural forest state. The study site covers an area of 8.32 km², which corresponds to more than 1.5 maps on a 1:5000 digital scale, in order to increase the applicability of the findings across the forest.

There are various tree species in the study area, including 10 types of coniferous tree such as *Pinus densiflora* and *Pinus koraiensis*, and 30 types of broad-leaved tree such as *Quercus mongolica* and *Quercus serrata*.

In this study, six standard survey plots were delineated within Chiaksan National Park, and one plantation forest survey plot was established outside the park. A total of seven survey plots within the study area were established to evaluate the quality of ALS-based ITD experiments. Point cloud data with a density of more than 20000 points per square meter were generated using handheld TLS technology. Within the survey plots, the number of trees (N), coordinates (X_t, Y_t), tree height (H_t), and DBH were observed and used to determine the optimal ITD algorithm based on ALS by forest type. The characteristics of the study site are shown in Fig. 2. The seven survey

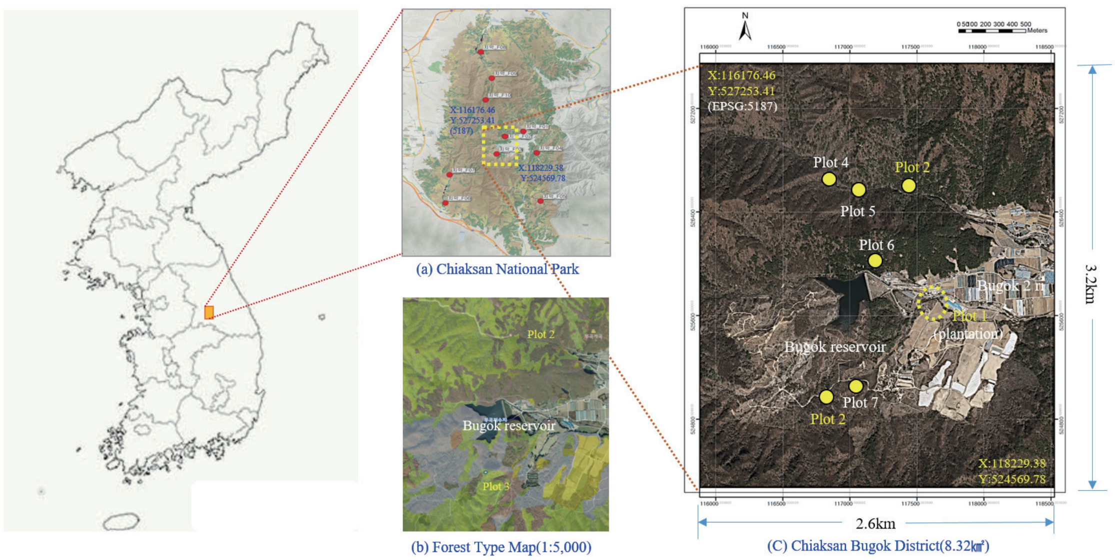


Fig. 2. (Color online) Description of study site (Chiaksan Bugok District).

plots in this study area consisted of one plantation (Plot 1) and six natural forest survey plots (Plots 2–7) within the national park to evaluate the applicability of the ALS-based ITD method, as shown in Fig. 3 and Table 1.[11,12]

There are three conifers (Plots 2, 4, and 6) and three broad-leaved trees (Plots 3, 5, and 7) for each forest type. The point density of ALS data is 67–125 points per square meter and the maximum tree height is 16.9–25.3 m.

2.2 Data acquisition

In this study, ALS was conducted on the study site to build a digital twin database for individual tree-based forest management using complete enumeration survey data. The ALS equipment used in this study was Leica CityMapper-2, a multisensor system consisting of hybrid oblique imaging and high-density LiDAR airborne sensors, as shown in Fig. 4.

In addition, DLS and TLS were also conducted in six survey districts within the study area for ALS-based tree entity extraction quality analysis. The TLS equipment used in this study was the handheld Leica BLK2GO, and DLS was by an L1 LiDAR sensor mounted on a DJI M300 RTK quadrotor drone to acquire point cloud data of the survey area.

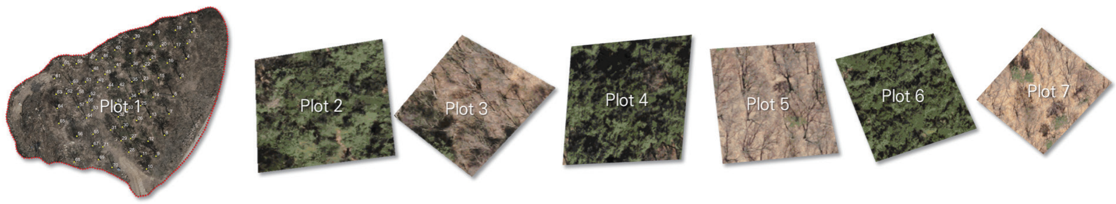


Fig. 3. (Color online) Plots in study site (Chiaksan Bugok District).

Table 1
Major characteristics of plots in study area (Chiaksan Bugok District).

Plot no.	Forest type	No. of trees	Area (m^2)	Point density (point/m^2)	Maximum tree height (m)	Remarks
Plot 1	CF	71	8159	74	17.5	Plantation forest
Plot 2	CF	102	851	67	23.6	Natural forest
Plot 3	DF	92	887	121	15.6	
Plot 4	CF	101	862	87	24.9	
Plot 5	DF	78	819	74	25.3	
Plot 6	CF	67	816	73	22.4	
Plot 7	DF	67	780	125	16.9	

*CF: coniferous forest, DF: broad-leaved forest

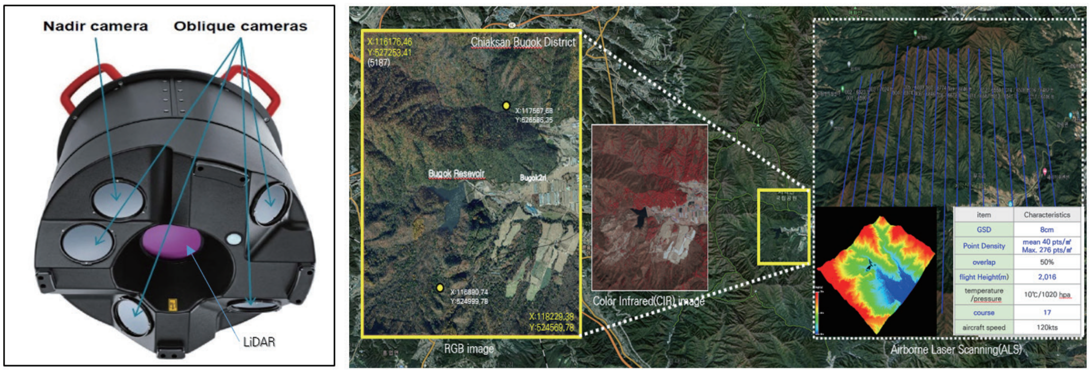


Fig. 4. (Color online) Data acquisition with airborne LiDAR photogrammetry.

2.2.1 ALS data acquisition

The ALS of the study area was conducted on April 10, 2022, before the forest vegetation growth rate accelerated, using the Leica CityMapper-2 system (Fig. 4). A total of 17 flight paths of high-density LiDAR point cloud data, along with hybrid oblique imaging and near-infrared (NIR) imaging, were adopted.

The average point density of ALS-based point cloud data was 40.4 points per square meter, which was used for ALS-based ITD experiments and the vertical structure analysis of forests, including tree height and crown information.(13)

Additionally, hybrid oblique and NIR images were analyzed through CV analysis to generate RGB and color infrared (CIR) orthoimages of the study site. These images were used for object-based forest type classification, allowing trees in the study site to be classified into coniferous and broad-leaved categories and the horizontal structure of the forest to be analyzed. Bentley Context Capture software was used for the CV analysis of the images.

As shown in Fig. 5, in addition to the orthoimage, the point cloud data generated from the CV analysis of the study site, DSM, and 3D mesh were also produced to visualize related data when building a tree-based forest management digital twin.(8)

2.2.2 TLS data acquisition

In this study, TLS was performed in six plots (Plots 2–7) established in the study area to determine the optimal parameters and perform the quality analysis of ALS-based ITD.(14)

In TLS, the 3D coordinates of the corners of each plot were measured using VRS GPS and the total station and used to match ALS and TLS data. The TLS equipment used in this study is Leica BLK2GO, a handheld LiDAR scanner that can easily scan trees in the survey area. This equipment, using simultaneous localization and mapping technology (SLAM), is applied to enable high-density LiDAR survey, making data acquisition easy. It is small and light, weighing less than 1 kg, including the battery. It has the advantage of allowing the easy survey of mountainous terrain with steep slopes, as well as areas that are difficult for people to access. In

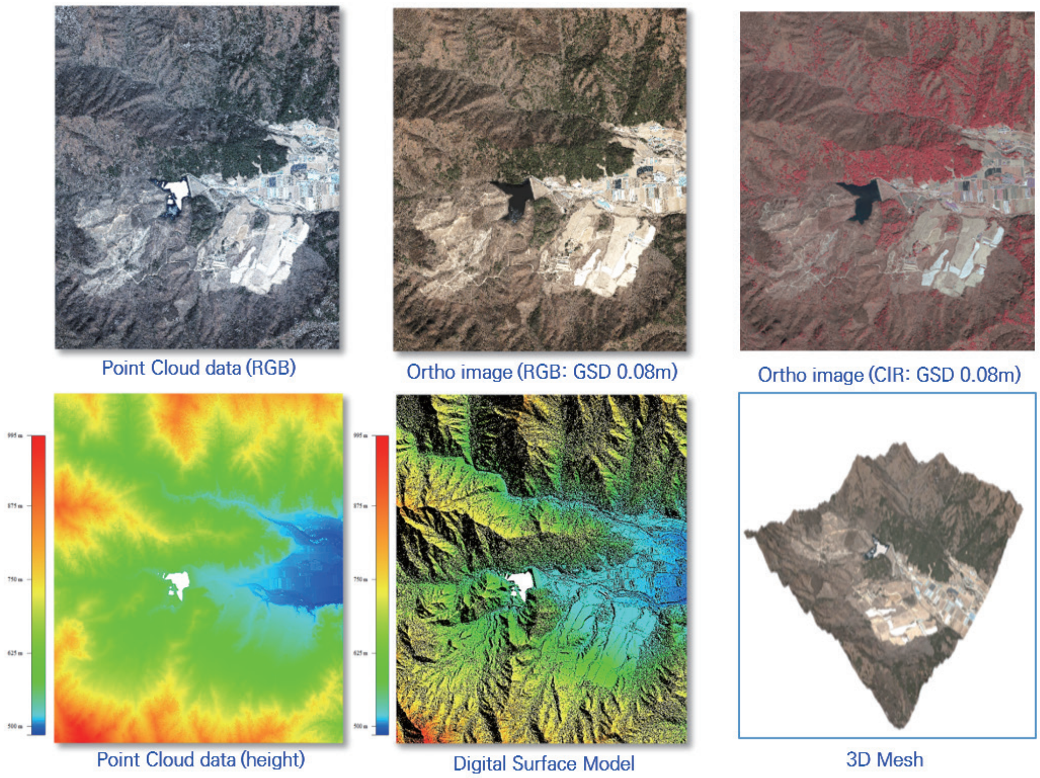


Fig. 5. (Color online) Outputs with CV analysis of five-direction aerial images.

this study, for the precise measurement of the study site, scanning was conducted three times, as shown in Table 2, to acquire TLS-based point cloud data.

Figure 6 shows the TLS-based point cloud data status for Plot 2 [(a) 2D PCD, (b) 3D PCD]. The TLS-based point cloud data shows a point density of more than 40,000 points per square meter on the ground, and the quality of the DEM is very high. However, depending on the scanning range of the equipment, the point density of tree crown data is relatively low; thus, for trees with a large tree height, the tree height tends to be smaller than that determined by ALS-based PCD, owing to the limitations of the scanning range.(15)

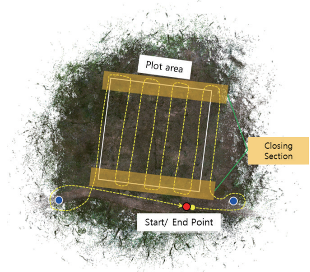
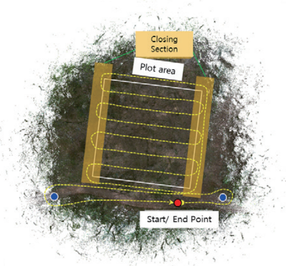
3. ALS-based Horizontal and Vertical Structural Surveys of Forests

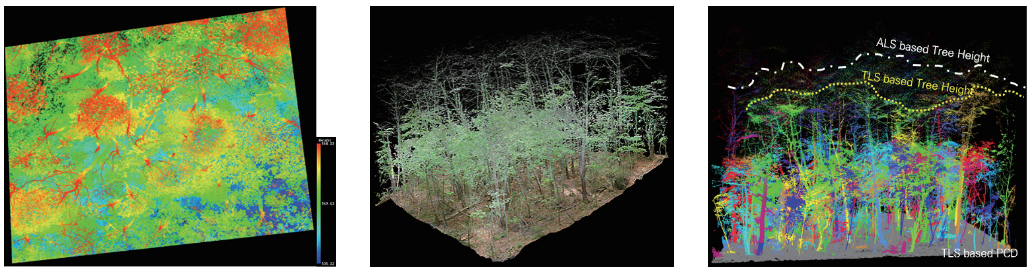
In this study, the total area of the study site (8.32 km^2), which is a natural forest within the national park, was targeted. The results of ITD of forest type and ALS-based PCD, which are information on the horizontal structure of forests, were used. As shown in Fig. 7, we performed ITD to generate the vertical structural information of the forest, such as *H* and *DBH*.

3.1 Object-based forest type classification using orthoimage

The horizontal structure of a forest is information that generally indicates the tree species and forest type included in the forest type map. In this study, CV analysis was performed on digital

Table 2
(Color online) TLS methodology with Leica BLK2GO in PLOT.

1st Scanning	2nd Scanning	3rd Scanning
		
- preliminary investigation - equipment inspection - GNSS control surveying	- scanner attitude calibration - closed section settings - equipment location definition	- data matching - inspection performance - checking for missing data - creating a scanning file



(a) (b) (c)

Fig. 6. (Color online) TLS-based point cloud data of Plot 2: (a) TLS-based 2D point cloud data (Plot 2: BLK2GO), (b) TLS-based 3D point cloud data (Plot 2: BLK2GO), and (c) difference in tree height (ALS VS TLS).

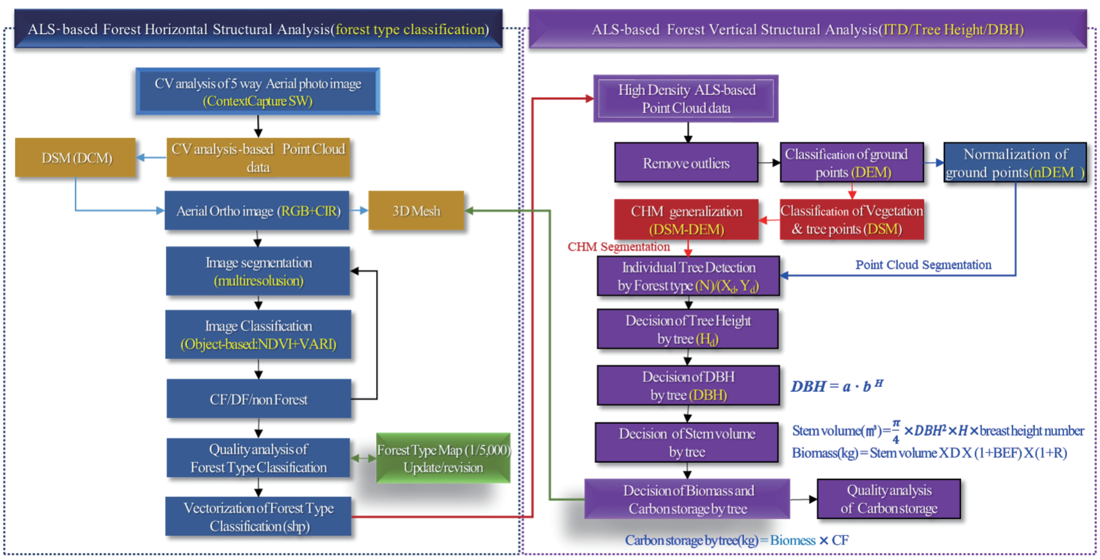


Fig. 7. (Color online) ALS-based forest structure analysis.

images acquired through ALS to generate RGB and CIR orthoimages, and on the basis of this, nonforest land was first classified through a vegetation index, which is the visible atmospherically resistant index (*VARI*), to distinguish forested vegetation areas from non-vegetated areas, and forest type classification was performed using the normalized difference vegetation index (*NDVI*).

The results of the forest type classification (coniferous forest, broad-leaved forest) of trees in the study area through object-based image analysis (OBIA) performed in this study are shown in Fig. 8.[16]

For the quality analysis of the object-based forest type classification results in the study area, 500 random points were generated for each clinical trial, and the quality evaluation for each forest type was performed using an error matrix.[17]

In this study, we improved the method using only the existing *NDVI* and first classified and analyzed nonforest land in the target area through *VARI*. As a result, the classification accuracy of broad-leaved trees was relatively improved, with a recall of 95.9%, a precision of 95.9%, and an $F1$ score of 0.959. Through this, we found that the object-based forest type classification

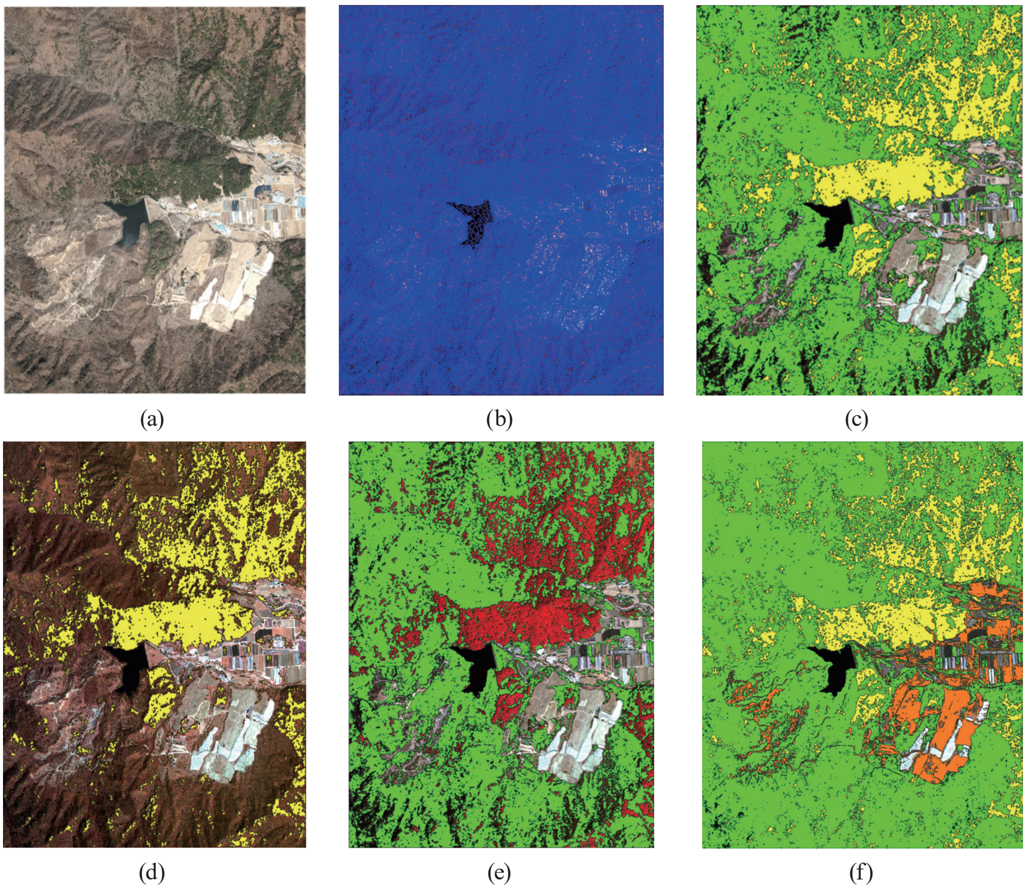


Fig. 8. (Color online) Result of object-based forest type classification of study area: (a) orthoimage of study area, (b) multiresolution segmentation, (c) forest type classification with assigned class (*NDVI* + *VARI*), (d) coniferous forest ($0.36 \leq NDVI \leq 1$), (e) broad-leaved ($0.28 \leq NDVI < 0.36$), and (f) CF + DF + nonforest (ground) ($0.32 \leq VARI$).

method based on orthoimages proposed in this study showed a reliability of more than 95%. The object-based forest type classification results of the study area were vectorized and used for ITD and the vertical structure analysis of ALS-based PCD.

3.2 ALS-based determinations of optimal ITD algorithm and parameters by forest type in natural forest

The vertical structural analysis of a forest is the process of generating tree height, *DBH*, and crown data. In this study, we determined the optimal algorithm and forest type parameters to perform ITD using high-density ALS data to convert from the previous ABA to the individual tree-based approach for the vertical structural analysis of forests.

In general, ITD algorithms using LiDAR data are classified into point cloud segmentation (PCS)[18,19] and CHM segmentation (CS).[20,21]

In this study, ITD experiments were conducted in two steps. In the first ITD experiment, we evaluated the applicability of the ITD algorithm to plantation forest (Plot 1: Fig. 3) comprised mainly of coniferous trees included in the study area.

In the second experiment, we determined the optimal ITD and parameters for each object-based forest type classification for the six natural forest survey areas (Plots 2 to 7: Fig 3) existing in the study area.

The number of trees (N), tree coordinates (X_t, Y_t), and *DBH* for each survey district were determined by cutting a stem cross section at a breast height of 1.2 m, starting from the ground surface of LiDAR data, using the TLS scan results for each survey district., and the most probable value was generated for trees with $DBH > 6$ cm.

In addition, the most probable value of tree height was measured by fusing TLS and ALS data to overcome the limitations of the scanning range of the TLS equipment. The ITD experiment for Plot 1, an ALS-based artificial forest, was conducted through the same process as shown in Fig. 9, and both methods showed an ITD quality of more than 90% (Table 3).

In the ALS-based ITD experiment, the CHM segmentation method showed a higher detection quality than the PCS method owing to the abundant tree canopy information in ALS data.

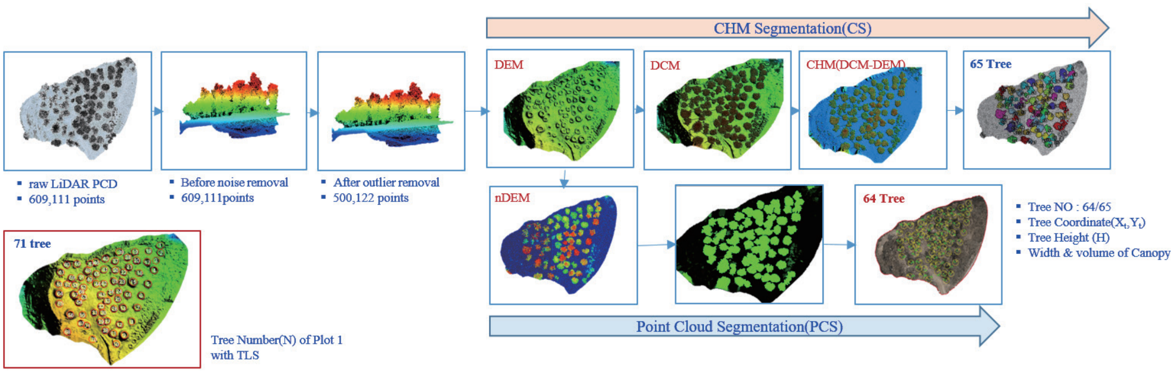


Fig. 9. (Color online) ITD process and results of Plot 1 (manmade forest).

Table 3
ITD quality analysis of Plot 1 (manmade forest).

ITD algorithm	Tree No. (Plot 1)	TP	FP	FN	Sum	Recall (%)	Precision (%)	$F1$ score
Point cloud segmentation (PCS)	71	61	3	10	74	85.9	95.3	0.9037
CHM segmentation (CS)		64	1	7	72	90.1	98.5	0.9412

In addition, on the basis of the results of Plot 1, which was an artificial forest, a second ITD experiment was conducted targeting the survey area in a natural forest (Plots 2 to 7).

In the ALS-based tree entity extraction experiment from a natural forest, the parameters with the highest quality were determined for each forest type through repeated experiments, changing the main parameters for each algorithm,[22–24] as shown in Fig. 10 and in the ITD experiment of this study. GreenValley International's LiDAR360 software was used.

In the ALS-based analysis of the quality of ITD from natural forests, recall, precision, and $F1$ score were analyzed using a confusion matrix, which is used as a classification performance evaluation index in machine learning.

As a result of analyzing the quality of ITD from natural forests using CHM segmentation, as shown in Table 4, all plots show an ITD quality of more than 70%. For coniferous trees with a *DBH* of 0.1 m or more (Plots 2, 4, and 6), the ITD quality was close to 80%. On the other hand, in the case of broad-leaved trees (Plots 3, 5, and 7), the quality of ITD was lower owing to the variety of tree species and the degree of bending being greater than that of coniferous trees.

3.3 Calculation of *DBH* using nonlinear regression equation

DBH is the diameter of a tree at a breast height of 1.2 m and is important information on the vertical structure of a tree along with its height. The direct measurement of the *DBH* of individual trees using ALS-based point cloud data is difficult owing to the lack of point density.

Therefore, in this study, the tree height data generated during the ALS-based ITD process was used to determine the *DBH* of the detected trees through the following nonlinear regression equation:

$$H = a \times DBH^{b} \rightarrow DBH = a \times b^{H}. \tag{1}$$

The determination of the optimal nonlinear regression equation for calculating *DBH* for each forest type was conducted on trees from six survey plots (Plots 2 to 7) in the Bugok District of Chiaksan National Park. Among these, trees with a small *DBH* due to a different forest type or because the point cloud was cut off owing to being located on the border of the survey area were excluded.

Through the TLS-based height data of 225 trees in the coniferous tree group (Plots 2, 4, and 6) and 225 trees in the broad-leaved tree group (Plots 3, 5, and 7) obtained in this way, the calculation formula for *DBH* for each forest type was determined as shown in Table 5.

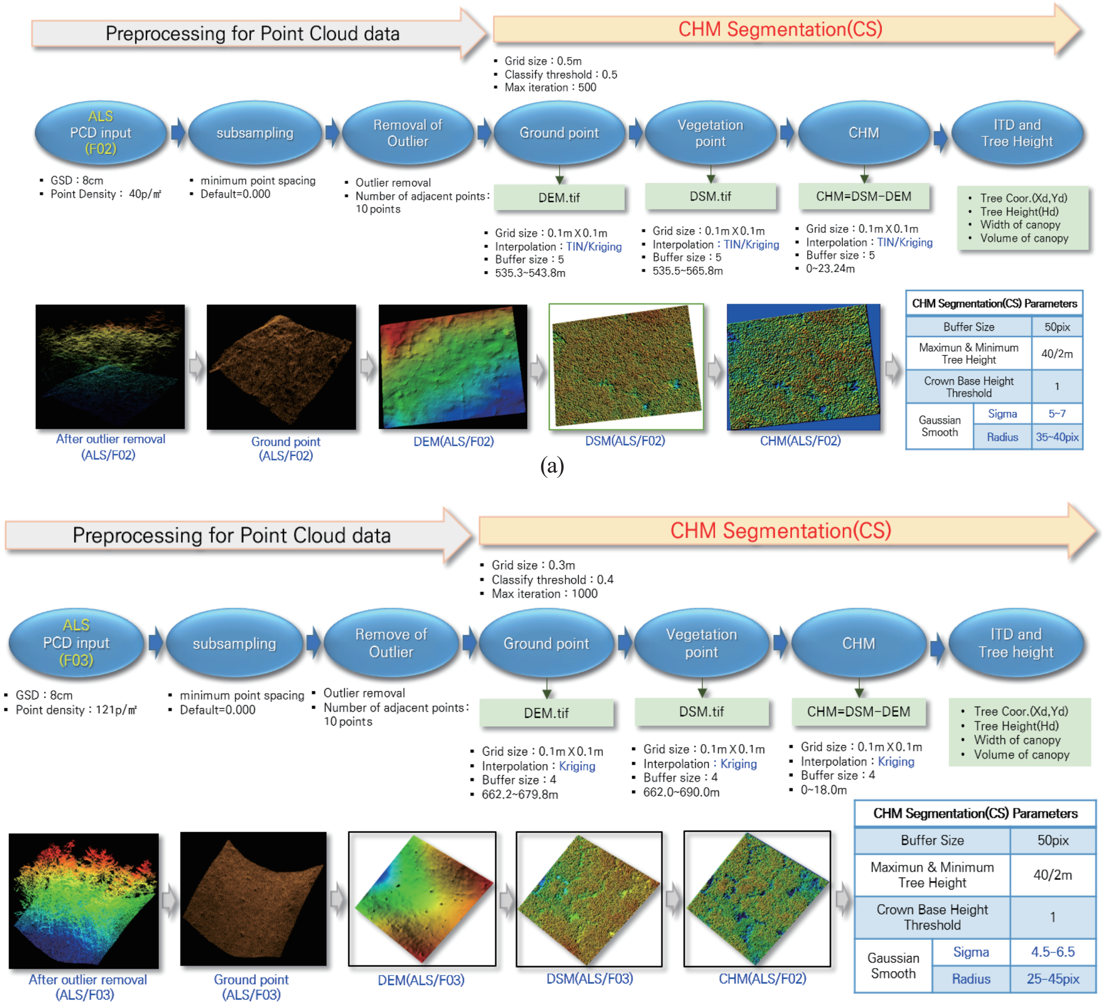
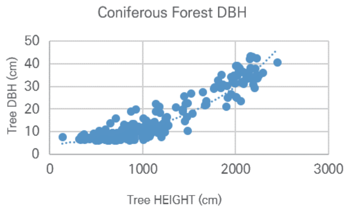
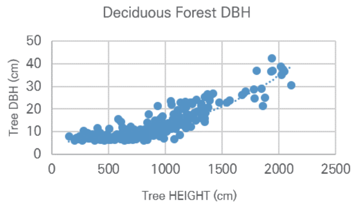


Fig. 10. Determination of optimal ITD methodology (CS) in accordance with forest type in natural forest: (a) coniferous and (b) broad-leaved forests.

Table 4
(Color online) Results of ITD quality analysis and optimal parameter determination through ALS-based CHM segmentation.

item		ALS based ITD Quality with CHM Segmentation			ALS based CHM segmentation parameter					
		Recall (%)	Precision (%)	F1 score	buffer size (pix)	Tree Height (m) Max	Tree Height (m) Min	Crown Base Height threshold	Gaussian smooth σ	Gaussian smooth Radius (pix)
CF	Plot 2	72.55	75.51	0.740	50	40	2	1	5	35
	Plot 4	72.28	76.84	0.745					5	35
	Plot 6	76.12	76.12	0.761					5.7	35
	DBH 〉0.1m mean	78.34	80.82	0.801					6.0	42
DF	Plot 3	71.74	74.16	0.737					4.5	25
	Plot 5	71.79	72.72	0.723					5.1	41
	Plot 7	74.63	74.63	0.746					5.8	35
	DBH 〉0.1m mean	76.13	77.49	0.768					7.0	43

Table 5
(Color online) Determination of nonlinear regression equation for calculating DBH.

Forest Type	Coniferous Forest	Broad-leaved Forest
No. of trees	225	225
Nonlinear Regression Equation	$DBH = 4.17809*1.000984^{H}$	$DBH = 4.686619*1.001002^{H}$
Regression Curve		
RMSE (cm)	±3.4	±3.2
R-squared	0.8563	0.7499

As shown in Table 5, the quality of the regression equation for calculating *DBH* was analyzed using the root mean square error (RMSE) of the *DBH* observed on the basis of TLS for each forest type and the *DBH* determined by the nonlinear regression equation.

As a result of the analysis, RSME for coniferous trees was +3.4 cm, which was slightly larger than that for broad-leaved trees (±3.2 cm). This result is due to a lack of data on trees with a small or large *DBH*. It is considered that it can be improved by increasing the amount of data, such as tree *DBH* or H, from forest type survey districts in the future.

4. Creation of a Digital Twin Database for Forest Management in the Bugok District of Chiaksan National Park

In this study, the results of multisensor-based aerial LiDAR surveying for the natural forest in the Bugok District (8.32 km²) of Chiaksan National Park were used. The method for creating horizontal and vertical structure data based on trees established through this study and the process for calculating the carbon storage capacity were performed using the same process as in Fig. 11. By doing so, a digital twin DB for forest management based on individual trees was constructed.

4.1 Creating a digital twin DB for forest management based on individual trees

A tree-based forest management digital twin system refers to a virtual space for forest management centered on three-dimensional forest management data for individual tree units using ALS data, A tree-based forest management digital twin can perform three-dimensional forest management by increasing the level of detail (LOD) of forest management data and can improve the ability to cope with forest disasters such as forest fires and landslides.

In this study, multidirectional images acquired through airborne laser surveying were used to perform object-based forest type classification to create boundaries between coniferous and broad-leaved forests.

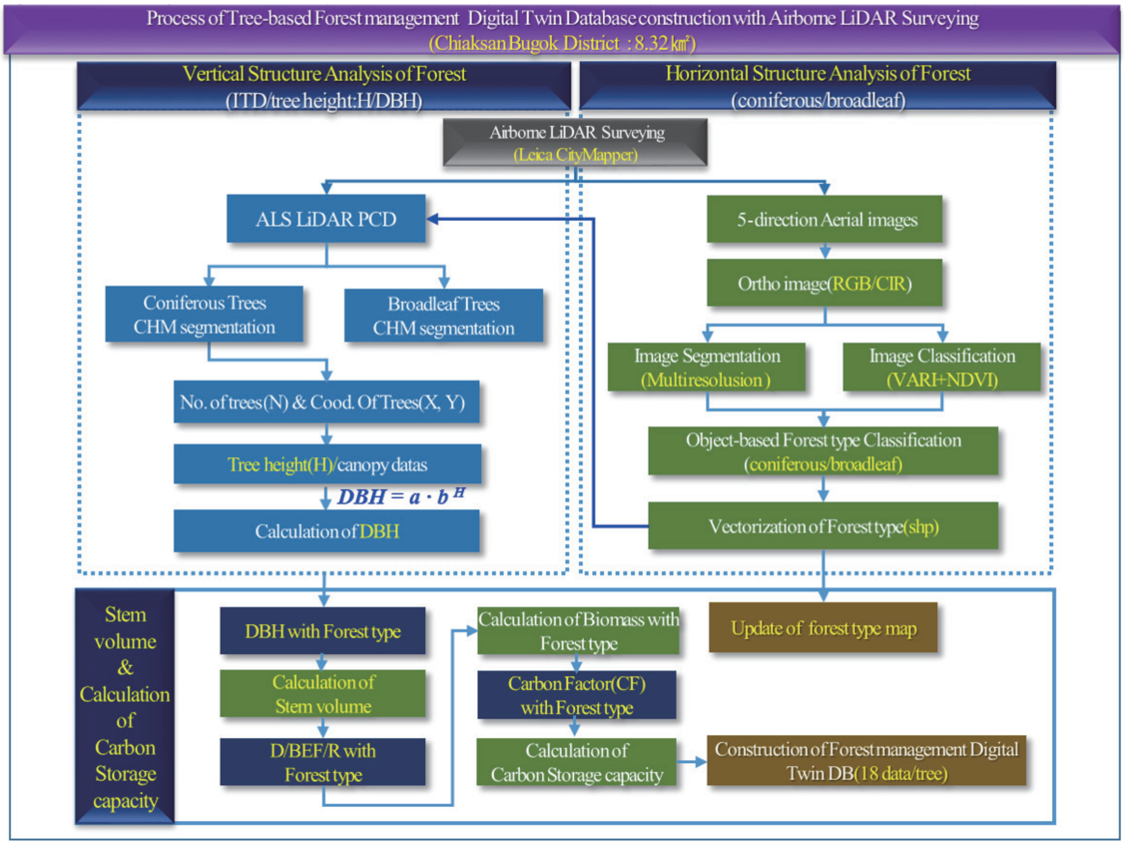


Fig. 11. (Color online) Process of tree-based forest management digital twin database construction with airborne LiDAR surveying data (Chiaksan Bugok District: 8.32 km²).

Using the generated boundary, we applied CHM segmentation, an optimal ITD methodology, to the high-density PCD acquired through airborne laser surveying to extract coniferous and broad-leaved forests in the entire study area by tree unit, and tree number, tree coordinates, tree height, and tree crown information were generated.

The *DBH* of the extracted trees was estimated using a nonlinear regression equation for each forest type. Using the *DBH*, the stem volume, biomass, and carbon storage capacity of each tree were calculated to create a forest management database for each tree unit for the entire area of the study area.

4.1.1 Postprocessing of object-based forest type classification

In this study, prior to ITD in the study area, RGB and CIR images were used to classify the forests in the study area into coniferous and broad-leaved trees through OBIA in order to apply different parameters for each forest type.

In the forest classification applied in this study, the nonforest part of the study area was first classified using *VARI*, and then the boundaries between coniferous and broad-leaved trees in the study area were created using *NDVI*.

Since the object-based forest type boundary is represented as a square in pixel units, a postprocessing step of the object-based clinical boundary was performed to correct this, as shown in Fig. 12, to finally create the boundary between the coniferous and broad-leaved forests for the research subject.

4.1.2 CHM generation and ITD by tree type

In this study, the ALS-based high-density PCD acquired from the entire study area were classified by forest type on the basis of the boundary generated through OBIA.

Next, ITD was performed by applying forest type-specific parameters of CHM segmentation, the optimal ITD methodology determined through this study.

In particular, in the process of ITD by tree species, deciduous conifers such as larch were identified using a large-scale forest map, and the boundaries of each forest were corrected. Then, a canopy height model (CHM) for each forest was created following the process shown in Fig. 13 for ITD.

In this study, ITD was performed through CHM segmentation applying the parameters in Table 4 using the ALS-based CHM for each forest area of the Bugok District of Chiaksan National Park, as shown in Fig. 13.

As a result of ITD in the research area, a total of 791,280 individual trees were extracted, including 293,154 coniferous trees and 498,126 broad-leaved trees (Fig. 14).

4.1.3 Carbon storage data generation for individual trees for forest management

In this study, we generated individual tree coordinates (*X*, *Y*), tree height (*H*), and crown information for each tree by tree species. Using the generated tree height, we calculated *DBH* through a nonlinear regression equation (Table 5).

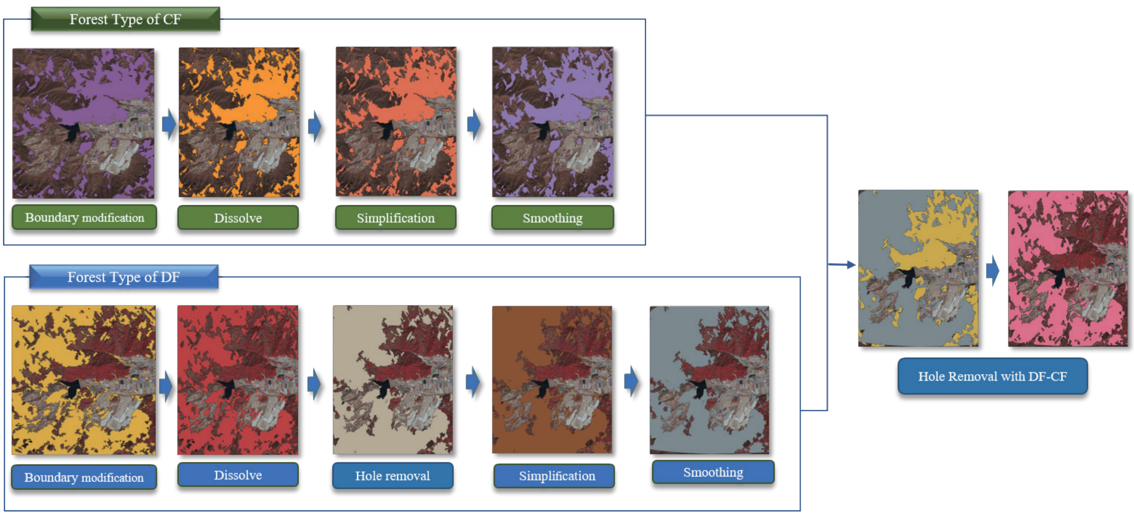


Fig. 12. (Color online) Postprocessing of object-based forest type boundary.

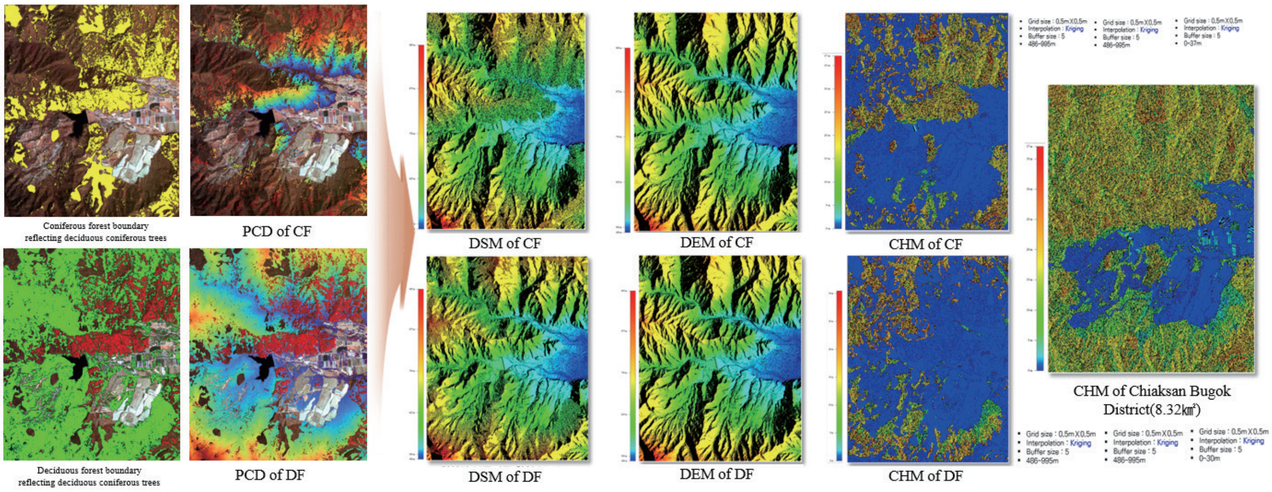


Fig. 13. (Color online) Canopy height model of Chiaksan Bugok District (8.32 km²).

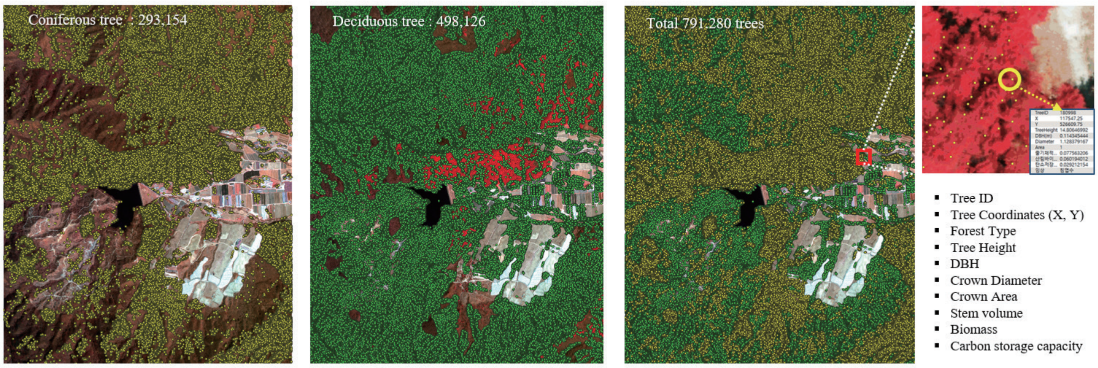


Fig. 14. (Color online) Results of ITD of Chiaksan Bugok District (8.32 km²).

Additionally, we estimated the stem volume of individual trees by applying species-specific breast height form factors to the tree height and *DBH* data obtained from ITD across the study area.

We then estimated the forest biomass and carbon storage capacity per tree by applying the forest biomass expansion and carbon conversion factors to the entire forest in the study area.

Through this process, we created a total of 18 forest management digital twin databases for each tree in the entire research area within the Bugok District of Chiaksan National Park. By extracting individual trees by forest type for the whole research site, we built a forest management database.

The statistical analysis results of the created database, as shown in Table 6, indicate that the average height of coniferous trees is greater than that of broad-leaved trees. However, the average *DBH* of broad-leaved trees is larger than that of coniferous trees, and the total stem volume is 2.16 times larger for broad-leaved trees. Furthermore, the biomass and carbon storage capacity of broad-leaved forests are more than twice those of coniferous forests, indicating that

Table 6
(Color online) Tree-based forest management database and statistical analysis of Chiaksan Bugok District (8.32 km^2).

<table>
<tr><th colspan="3">General data(3)</th><th colspan="2">Horizontal structural data(2)</th><th colspan="5">Vertical structural data(5)</th></tr>
<tr><td rowspan="2">Tree ID</td><td>X</td><td>Y</td><td rowspan="2">Tree species</td><td rowspan="2">Forest Type (CF/DF)</td><td rowspan="2">Tree Height(m)</td><td rowspan="2">DBH(cm)</td><td colspan="3">Crown</td></tr>
<tr><td colspan="2">EPSG:5187</td><td>diameter</td><td>area</td><td>volume</td></tr>
<tr><th colspan="10">Cabon Storage Capacity data(8)</th></tr>
<tr><td colspan="3">Stem Volume(m^3)</td><td colspan="7">• Tree-based Stem volume(㎥) = $\frac{\pi}{4} \times DBH^2 \times H \times$ Breast height form factor
• Breast Height form factor with forest type</td></tr>
<tr><td colspan="3">Biomass(kg)</td><td colspan="7">• Tree-based Biomass (kg) = Stem volume $\times D \times BEF \times (1+R)$
• D, BEF, R with forest type</td></tr>
<tr><td colspan="3">Carbon Storage Capacity(kg)</td><td colspan="7">• Tree-based Carbon storage capacity (kg) = tree-based Biomass × Carbon Fraction(CF)
• CF with forest type</td></tr>
<tr><th>Forest Type</th><th colspan="3">Nonlinear regression EQ. for DBH</th><th>Basic density (D:kg/㎥)</th><th colspan="2">Biomass expansion coefficient (1+BEF)</th><th>Root-shoot ratio (1+R)</th><th colspan="2">Carbon Fraction (CF)</th></tr>
<tr><td>CF</td><td colspan="3">DBH = 4.178090x1.000984^H</td><td>0.47</td><td colspan="2">1.29</td><td>1.28</td><td colspan="2">0.4853</td></tr>
<tr><td>DF</td><td colspan="3">DBH = 4.686619x1.001002^H</td><td>0.80</td><td colspan="2">1.22</td><td>1.48</td><td colspan="2">0.4798</td></tr>
</table>

<table>
<tr><th rowspan="2">Forest Type</th><th rowspan="2">Number of Trees</th><th rowspan="2" colspan="2">Distribution of Tree Height(m)</th><th rowspan="2" colspan="2">Distribution of DBH(cm)</th><th colspan="3">Total Carbon storage capacity</th></tr>
<tr><th>Stem Volume (㎥)</th><th>Biomass (ton)</th><th>Carbon storage Capacity(ton)</th></tr>
<tr><td rowspan="3">Coniferous Tree</td><td rowspan="3">293,154</td><td>Max</td><td>38.43</td><td>Max</td><td>77.21</td><td rowspan="3">119,775.17</td><td rowspan="3">92,953.20</td><td rowspan="3">45,110.18</td></tr>
<tr><td>Min</td><td>6.95</td><td>Min</td><td>5.97</td></tr>
<tr><td>Mean</td><td>19.80</td><td>Mean</td><td>19.61</td></tr>
<tr><td rowspan="3">Deciduous tree</td><td rowspan="3">498,126</td><td>Max</td><td>31.79</td><td>Max</td><td>92.12</td><td rowspan="3">253,401.83</td><td rowspan="3">353,862.47</td><td rowspan="3">169,853.99</td></tr>
<tr><td>Min</td><td>6.28</td><td>Min</td><td>5.93</td></tr>
<tr><td>Mean</td><td>15.54</td><td>Mean</td><td>21.52</td></tr>
<tr><td>Total</td><td>791,280</td><td colspan="2">-</td><td colspan="2">-</td><td>373,177.00</td><td>446,815.67</td><td>214,964.17</td></tr>
</table>

DBH affects carbon storage more than tree height. This suggests that broad-leaved forests are more beneficial than coniferous forests in terms of carbon storage capacity.

In this study, we conducted ALS-based ITD in the natural forest at the research site and generated 18 types of vegetation structure and carbon storage data per tree. Our work demonstrates the potential for constructing an ALS-based individual tree forest management digital twin database.

4.2 Creating a forest management data thematic map using a forest management digital twin DB

In this study, we confirmed that it is possible to provide intuitive information necessary for forest management, such as digital-based tree unit visualization data, by creating a thematic map using a total of 18 forest management digital twin databases for individual trees.

As shown in Fig. 15, through the tree-based tree height thematic map of the research area, it is possible to confirm the difference between the tree height distributions of coniferous and broad-leaved forests in the research area and the region where very tall trees grow in large numbers in accordance with forest type.

Additionally, the individual tree-based forest management digital twin database can be used to create 2D and 3D thematic maps of *DBH*, stem volume, biomass, and carbon storage capacity.

Through this, information on the creation of forest resources and information required for effective individual tree-based forest management can be easily checked (Fig. 16).

4.3 Establishment of a pilot of digital twin for individual tree-based forest management

In this study, we classified forest types across the entire research area in the Bugok District of Chiaksan National Park using the results of multisensor-based airborne laser surveying and ITD by forest type through CHM segmentation.

We then constructed a database containing 18 types of forest management structure information and carbon storage for each tree. Through this study, a pilot of the forest management digital twin platform was built by linking the forest management digital twin

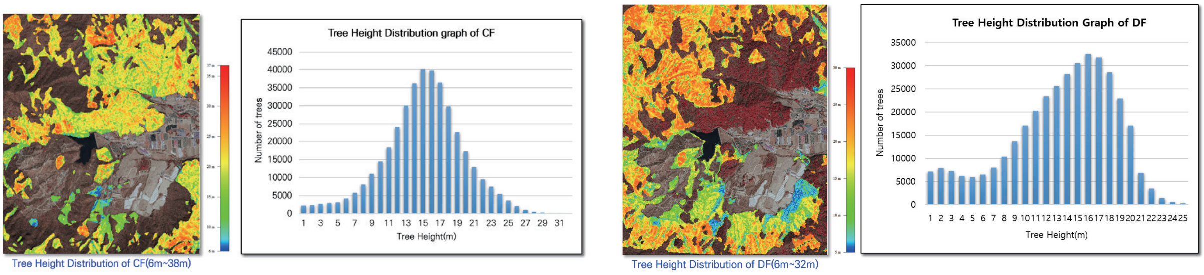


Fig. 15. (Color online) Tree height thematic map with forest type.

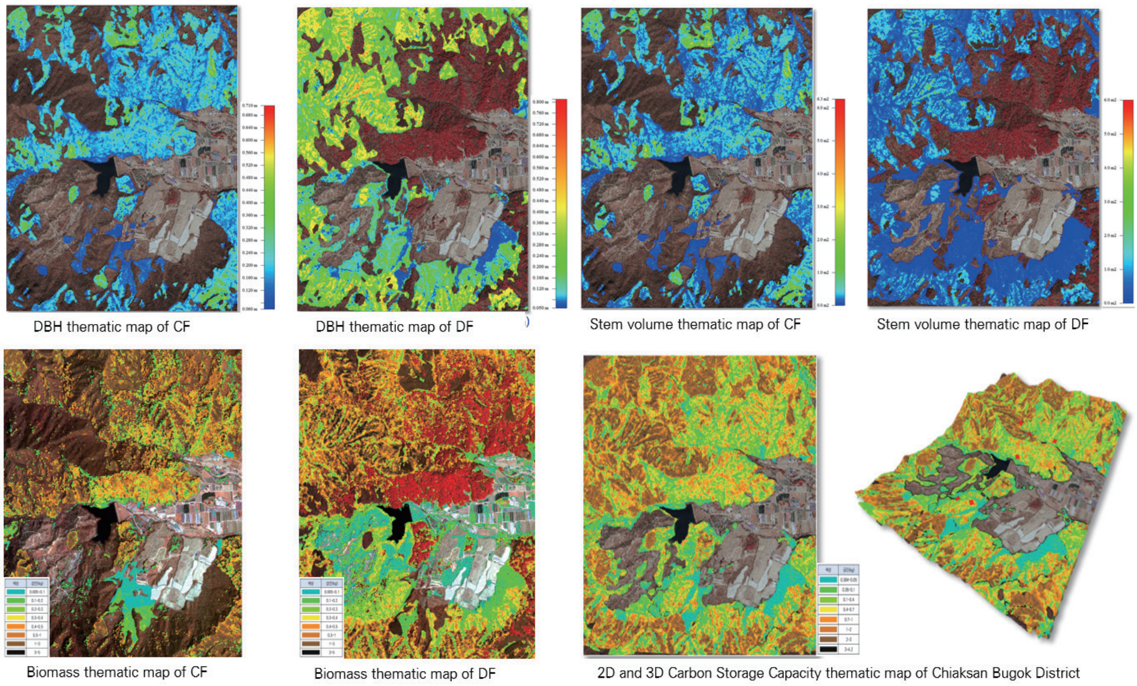


Fig. 16. (Color online) 2D and 3D thematic maps with forest management database (tree height/DBH/stem volume/biomass/carbon storage capacity).

database based on the entire tree and the related thematic maps.

For the pilot construction of the forest management digital twin platform, the LOD of the forest management database, built using the open-source cesium spatial information platform, was enhanced by applying a 3D tree model for each clinical area based on Unreal, a tool recently popular in gaming. Additionally, 3D tiles were applied to improve the visualization performance and reduce the weight of the 3D model for each tree (Fig. 17).

In addition, we plan to implement a simulation function for responding to forest disasters such as landslides and forest fires by linking the tree unit forest management digital twin database constructed through this study with existing meteorological and soil-related topic information.

Fig. 17. Pilot construction of Unreal-based tree unit forest management digital twin.

5. Conclusion

In this study, a total of 18 types of forest management information were made into a DB by applying carbon absorption coefficients to the horizontal structure information of forests generated using ALS-based aerial images and CIR images and the vertical structure information of forests generated using high-density PCD. The main conclusions drawn through this study are as follows.

1) Object-based forest type classification was performed using an orthoimage, and a classification accuracy of more than 95% was achieved for both coniferous and broad-leaved trees.
2) The ALS-based optimal ITD algorithm was established, and an ITD quality of 73% was shown for each forest type in a natural forest through CHM segmentation.
3) *DBH* was calculated by determining a nonlinear regression equation for each forest type using the tree height of the survey districts and showed RMSE of more than ±3 cm for each forest type, but it is believed that this can be improved by expanding the survey districts in the future.
4) By applying the optimal ITD methodology established in this study, the forest types of the entire study area in the Bugok district of Chiaksan National Park were classified, and individual coniferous trees (293194 trees) and broad-leaved trees (498126 trees) were classified through CHM segmentation.
5) Ultimately, a total of 791280 tree entities were extracted, and a total of 18 forest management digital twin databases were created for all trees.

As mentioned above, the object-based forest type classification technology established through this study, individual tree vertical structure analysis through ALS-based ITD, and carbon storage calculation technology were used to generate forest management information based on total data, and a digital twin for individual trees forest management was built.

In addition, the established forest management digital twin databases are expected to be widely used as decision-making support data that can provide predictive information through cause analysis and simulation in the future when various forest disasters and forest damage, such as forest fires and landslides, occur.

Acknowledgments

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